JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 07 Issue 02
2024
Research Article
https://doi.org/10.56979/702/2024

Internet of Medical Things (IoMT) Enabled Intelligent System for Chronic Disease Prediction Using Deep Machine Learning in Healthcare 5.0

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Received: July 12, 2024 **Accepted:** August 23, 2024 **Published:** September 01, 2024

Abstract: Accurately diagnosing human diseases is still challenging, even with the advances in Healthcare 5.0, especially with chronic diseases. The Internet of Medical Things (IoMT) has grown quickly worldwide, from tiny wearables to extensive applications in many different industries. Osteoarthritis (OA) is a prevalent chronic disease that has a major negative influence on life quality, especially in older people. Osteoarthritis is a common chronic joint disease that contributes significantly to morbidity and disability globally. It is the most frequent kind of OA. Knee Osteoarthritis (KOA) has a significant negative influence on the quality of life for those affected and presents an increasing challenge to public health systems as the world's population ages and life expectancy rises. Even though the precise causes of osteoarthritis (OA) are yet unknown, the complicated condition frequently affects joints that experience heavy weight and repetitive action. The knee joint is particularly susceptible because of its intricate structure and function as a weight-bearing joint our work investigates the use of deep machine learning techniques, including transfer learning, with X-ray image datasets to predict KOA in an Internet of Medical Things (IoMT) enabled system. This strategy is in line with the ideas of Healthcare 5.0, which places a strong emphasis on using cutting-edge technology to provide individualized, patient-centered care. This method makes use of the ResNet 18 architecture and transfer learning to produce precise and effective predictions from knee X-ray images. Our system's integration with the Internet of Medical Things (IoMT) facilitates real-time data processing and gathering, improving the predictive model's usability and accessibility in clinical settings. Using a dataset of knee X-ray images, the suggested model was trained and validated, yielding a high training accuracy of 98.26% and a validation accuracy of 95.79%. These findings support the model's efficacy in correctly diagnosing osteoarthritis, facilitating prompt diagnosis and treatment. Our results highlight the potential of IoMT and deep machine learning to improve personalized healthcare, especially for the treatment of long-term conditions like osteoarthritis. By incorporating these technologies into Healthcare 5.0 frameworks, it may be possible to improve outcomes and lessen the burden of chronic disease while providing more focused and patient-centered care. We seek to improve OA early diagnosis and customized therapy by utilizing IoMT and state-of-the-art deep machine learning algorithms, utilizing x-ray image data for improved healthcare results.

Keywords: Chronic Disease; Internet of Medical Things (IoMT); Deep Machine Learning; Osteoarthritis; Healthcare 5.0; Transfer Learning; Edge Technology.

1. Introduction

Osteoarthritis (OA), a chronic degenerative disease of the joints and14 million Americans suffers from it [1]. It causes pain, stiffness, and loss of movement. Even with the disease's enormous societal cost and widespread incidence, little is known about its pathophysiology. Moreover, the paucity of disease-modifying therapies is partly due to our inability to accurately measure early progression.

Chronic diseases, another name for non-communicable diseases (NCDs), are defined by their lengthy duration and slow progression. Diabetes, chronic respiratory disorders, cardiovascular disorders like hypertension, coronary heart disease, stroke, and arthritis are all included in this category [2]. The timely treatment of chronic diseases is facilitated by early diagnosis, which has a substantial positive impact on patient outcomes. Chronic illnesses are a big burden on the global healthcare system, driving up mortality rates and driving up costs, with many patients having to spend more than 70% of their income on treatment [3]. As a result, lowering the chance of dying from these diseases continues to be a top concern, and developments in medicine keep making it easier to obtain crucial health information.

Osteoarthritis, or OA, is one type of arthritis that affects joint function and produces pain. Although osteoarthritis (OA) was formerly believed to be the consequence of aging-related wear and tear, it is now understood to be a complex disease involving joint inflammation, bone remodeling, and cartilage degradation between the bones.

The most prevalent kind of arthritis, osteoarthritis, affects over 240 million individuals worldwide, 32 million of whom are Americans. OA, which affects the hands, feet, hips, and knees, was a disability that affected 7% of the population in 2020 [4].

The most prevalent kind of arthritis, osteoarthritis (OA), affects an estimated 302 million people globally [5-6], and it is the main cause of impairment for older persons. The appendicular joints that are most frequently impacted are the hands, hips, and knees. Osteophyte production, cartilage degradation, bone remodeling, and synovial inflammation are some of the joint-wide pathologies that characterize osteoarthritis (OA), which can cause pain, stiffness, swelling, and a loss of normal joint function.

One prevalent kind of arthritis that affects joints is osteoarthritis, sometimes referred to as degenerative joint disease or OA. It happens when the cartilage lining joints ages and becomes worn down, rubbing the bones against one another during activity. Smooth cartilage serves as a lubricant and shock absorber, enabling bones to move securely and smoothly. When a joint moves in osteoarthritis, the cartilage deteriorates and the bones rub against one another [7].

While osteoarthritis can affect every joint in the body, it usually begins in the hands, hips, neck, or cervical spine. Lower back, or lumber, as seen in Figure 1.

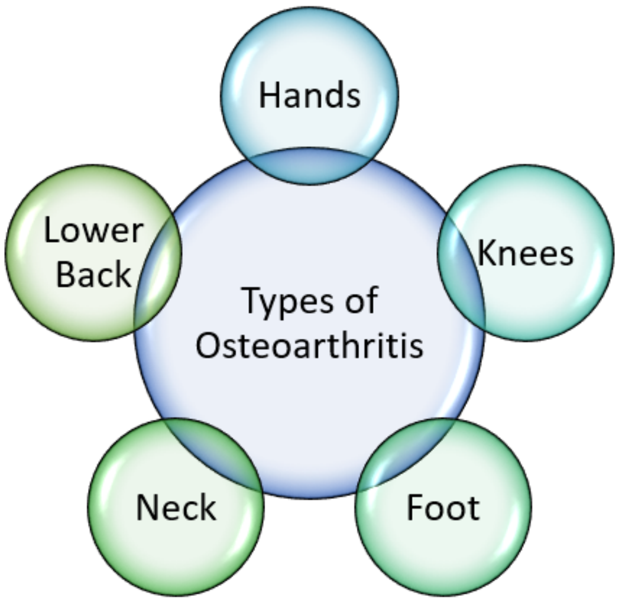

Figure 1. Types of Osteoarthritis

By far the most prevalent joint ailment is osteoarthritis (OA). Over 300 million people worldwide are impacted, experiencing physical disability and anguish [8]. Hip and knee replacements account for the majority of the medical costs associated with OA, which has been estimated to cost Western countries up to 2.5% of GDP overall [9]. Although OA can affect any synovial joint in theory, knee OA is the most common type of OA in practice [10].

2019 reported 528 million cases of osteoarthritis worldwide; women made up 60% of the affected population, while those over 55 made up 73%. The joints primarily afflicted were the hand and hip. For

344 million people with moderate to severe severity, rehabilitation may be helpful. Because of aging demographics, obesity, and accident rates, prevalence is predicted to increase.

Conditions affecting the bones, muscles, joints, and certain connective tissues are categorized as musculoskeletal conditions. These conditions include juvenile arthritis as well as long-term (chronic) conditions as gout, osteoarthritis, rheumatoid arthritis, osteoporosis, or osteopenia [11].

Factors that cause and increase risk. A person's risk for OA is determined by the interaction between two subgroups of risk variables. Age, gender, obesity, genetics, and diet are risk variables that are unique to each patient. Joint-specific risk factors include trauma, misalignment, and excessive joint loading [12]. In 2023, the number of Australians living with a disabilities due to osteoarthritis was 142840, or 4.44 per 1000 people, or 4.7% of the nonfatal burden [13], which is depicted by Figure 2.

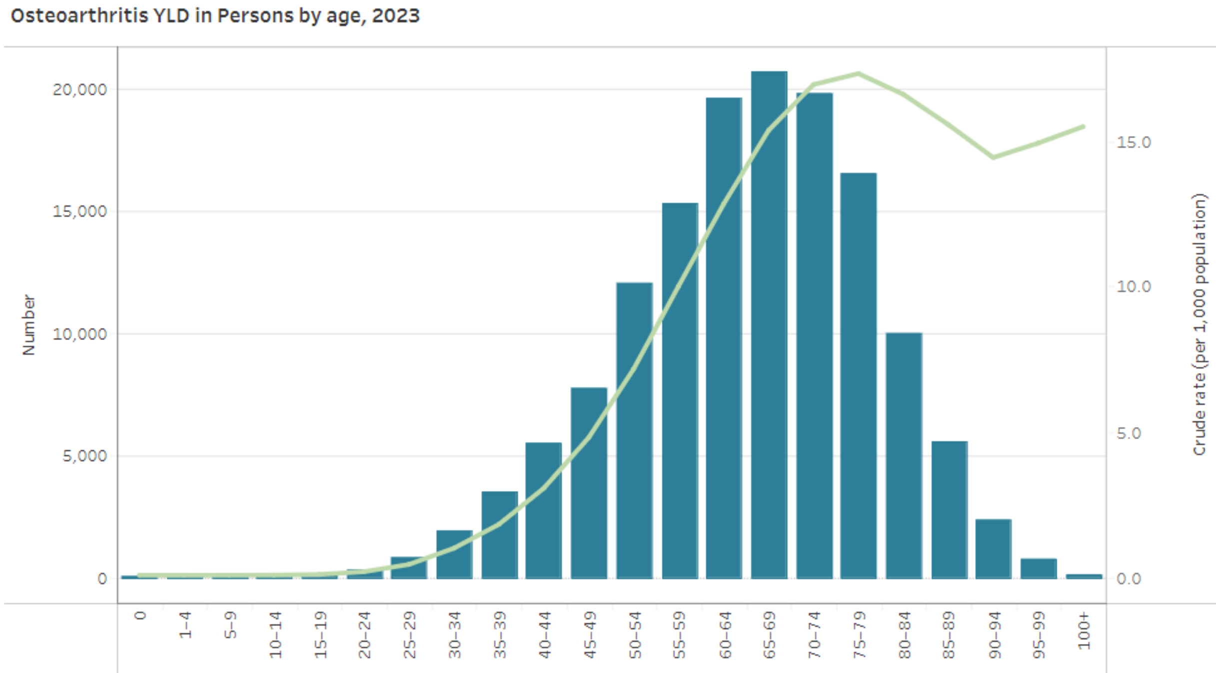

Figure 2. Burden of disease due to osteoarthritis, by age and sex, 2003, 2011, 2015, 2018 and 2023 [13]

Osteoarthritis is recognized to be more likely to occur in the following risk factors [14], provided in Figure.3.

Osteoarthritis (OA) is a kind of arthritis that affects the hands, feet, knees, hips, and other joints. It also impairs function. With an estimated 32 million Americans and over 240 million people worldwide affected, it is the most prevalent type of arthritis. Female sex, obesity, prior joint traumas, anomalies in the anatomy of the joints, and having family members with OA are risk factors for osteoarthritis (OA). Joint pain that worsens with movement and goes away with rest is one of the symptoms, as is temporary stiffness following inactivity. Bone spurs and narrowing of the joint spaces may be seen on X-ray imaging. A regular exercise regimen, physical therapy, weight loss, and patient education are all part of the treatment plan, which attempts to enhance joint function and lessen symptoms As first-line treatments for osteoarthritis (OA), NSAIDs, acetaminophen, and narcotic painkillers are frequently used. Injections of hyaluronic acid and steroids may help reduce edema and discomfort. Patients who experience chronic pain and loss of function may benefit from joint replacement surgery [15].

Currently, a clinical history, physical examination, and, if necessary, X-ray imaging (radiography) are used to diagnose OA in primary care. Unfortunately, accurate OA prognosis assessment is not possible with the widely accessible diagnostic techniques currently in use. This is a significant limitation as it affects both recruiting to OA disease modifying drug development studies and the design of appropriate therapeutic measures [16]. Adding Magnetic Resonance Imaging (MRI) to this diagnostic chain could be an improvement, but MRI is expensive, time-consuming, hard to come by, and not suitable for widespread use [17].

Although getting older may raise one's risk of developing osteoarthritis (OA), this condition is not a given. Reducing the disability related to OA requires early diagnosis and proactive intervention. A combination of clinical evaluations, radiographic exams, and the discovery of physiological biomarkers associated with osteoarthritis (OA) are necessary for an accurate diagnosis [18-19]. Imaging techniques that are useful for visualizing the cartilage and structure of joints include computed tomography (CT), MRI, X-ray imaging, and arthroscopy [20]. These techniques produce intricate anatomical images that show the physical alterations linked to OA. They are limited, although, in their ability to evaluate the cartilage's functional condition, which is essential for comprehending how the disease advances. A growing number of biomarkers are being utilized to diagnose osteoarthritis (OA), including C-reactive protein, serum cartilage oligomeric matrix protein, and interleukin-1 these biomarkers may offer more information on the molecular mechanisms behind OA. Nevertheless, their efficacy as stand-alone diagnostic tools may be limited if they lack the sensitivity to identify OA in its early phases [21].

Figure 3. Risk Factors of Osteoarthritis

1.1. Imaging techniques for Osteoarthritis

1.1.1. Radiographs

Radiographs are commonly used to assess the structural changes associated with osteoarthritis (OA), despite the fact that OA can be clinically diagnosed without imaging [22-23]. This is because radiographs are readily available, inexpensive, and easy to interpret. Bony characteristics of osteoarthritis (OA) such as cysts, subchondral sclerosis, and marginal osteophytes are effectively visible on radiographs. They also show narrowing of the joint space, which is indicative of meniscal extrusion or injury and cartilage loss. Osteophytes, or bone growths, are the most prevalent radiographic criteria used to diagnose structural OA because they typically develop before joint space constriction. These imaging modalities are essential because they offer unambiguous, reasonably priced insights into the course of the illness, enabling medical professionals to diagnose and treat OA more skillfully.

Radiographs provide a useful perspective on the degree of joint degeneration by examining changes in bone structure and joint space, which might inform treatment decisions

The use of radiography or X-rays to observe pain and restlessness is the basis for diagnosing and treating KOA [24–25]. Important features visible on X-rays include osteophytes, joint space narrowing (JSN), cyst development, and subchondral sclerosis. JSN is the term used to describe the absence of cushioning cartilage between knee joints. Osteophytes are bony growths on bones or joints, while subchondral sclerosis is an abnormal thickening of the bone [25]. Figure 4 shows several imaging techniques pre-sent.

Using radiographic images (X-rays), the Kellgren and Lawrence (KL) grading system is a well-known semi-quantitative technique for determining the degree of knee osteoarthritis (KOA). Based on the severity of osteoarthritic alterations seen in the pictures, such as joint space narrowing, osteophyte formation, and sclerosis, it awards ordinal grades [26].

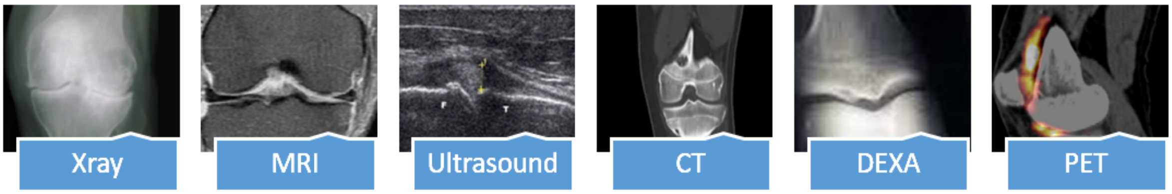

Figure 4. Imaging techniques for the diagnosing Osteoarthritis

1.1.2. MRI

When diagnosing individuals with osteoarthritis, it is essential to precisely identify and describe articular cartilage abnormalities. For a noninvasive examination of articular cartilage, magnetic resonance imaging (MRI) is the most accurate modality, albeit radiography is still the primary choice [27]. Because of its 3D format and soft-tissue contrast, magnetic resonance imaging (MRI) is a vital study tool for osteoarthritis, helping to clarify the etiology and course of the disease [28].

In regular clinical care and clinical trials, conventional radiography is still the major imaging modality. On the other hand, research on osteoarthritis has found that magnetic resonance imaging (MRI) is an essential tool [29]. Due to radiography's shortcomings, which include its lack of specificity, insensitivity to changes, and difficulties with reproducibility in longitudinal investigations brought on by positioning problems, MRI [30], is preferred. In contrast to X-rays, which are primarily used to examine bone structures, magnetic resonance imaging (MRI) offers detailed images of both osseous and non-osseous components, enabling researchers to capture the many osteoarthritis phenotypes [31-32]. These phenotypes include differences in joint and periarticular tissue involvement, among other anatomical and clinical manifestations of the disease that are not discernible on radiography.

MRI contributes to a more sophisticated understanding of osteoarthritis by enabling phenotypic characterization. This enables patient categorization based on patterns and structure of the disease, such as atrophic versus hypertrophic phenotypes, or progressors against non-progressors [33-34]. As was recently shown by employing machine learning techniques to find illness patterns, this distinction is very important for enhancing treatment plans and bettering patient outcomes.

1.1.3. Ultrasound

Osteoarthritis (OA) is a disease that requires the use of well-established diagnostic procedures. Due to recent advances in high-resolution technology, ultrasonic testing (US) has become an important test. Although less popular in the past, US has become important in OA research and treatment due to its ability to visualize data in multiple planes. During examination, ultrasound can accurately characterize and quantify morphological changes in the meniscus, femur bone, and bone surface as a feature [35].

Ultrasound also has some advantages over other tests, such as the ability to identify abnormalities and visualize structures such as hyaline cartilage in the femur. Few contraindications, low cost and no ionizing radiation are its advantages [36]. Given the effectiveness of ultrasound compared with other modalities, more and more studies will use ultrasound as a first-line method to identify changes in knee OA [37]. Ultrasonography is often compared with other tests or used to facilitate diagnosis. Many studies have observed a significant correlation between ultrasound and radiographic OA features; ultrasound is more sensitive than radiography for osteophytes [38].

1.1.4. CT

Computed Tomography CT can produce three-dimensional pictures that show the bone tissues with a radio density contrast. This is helpful in OA, despite the fact that it exposes the patient to ionizing radiation [39-40], and increases patient burden by necessitating repeated imaging tests and possibly higher expenditures [41].

The use of 3D imaging modalities to confirm the diagnosis of knee osteoarthritis (OA) is encouraged by recent clinical guidelines from the American College of Radiology (ACR) and the European League against Rheumatism (EULAR) [42-43]. As second-line diagnostic techniques, these guidelines suggest modalities including computed tomography (CT) for evaluating bone structures and magnetic resonance imaging (MRI) for analyzing soft tissues. Imaging techniques are essential in open access research, even outside of their therapeutic uses. Guidelines from the Osteoarthritis Research Society International (OARSI) recommend using MRI and CT in OA clinical trials to improve understanding of the condition and evaluate therapy effectiveness [44]. These imaging modalities enhance both diagnostic and research endeavors by offering comprehensive insights into the structural alterations linked to OA.

Musculoskeletal CT methods, such as dual-energy, 4-dimensional, and cone-beam CT, have become an important diagnostic tool for gout, trauma, and the characterization of pathologic biomechanical states. In addition to improving spatial resolution for osseous microstructures, these approaches can assess biomechanical derangements of peripheral joints, visualize and quantify monosodium urate crystals in gout, and increase picture quality in bone densitometry, contrast-enhanced arthrography, and bone marrow imaging [45].

1.1.5. DEXA

Bone mineral density is measured using dual-energy X-ray absorptiometry (DEXA), a widely used diagnostic tool. DEXA helps identify individuals who may have osteoporosis by assessing bone density, allowing for timely intervention and disease management [46]. Poor bone density and low bone mineral density (BMD) in spine patients are associated with a higher incidence of postoperative mechanical complications. As with all medical procedures, preliminary assessment of the patient's underlying condition is important. Currently, dual-energy X-ray absorptiometry (DXA) is considered the gold standard for determining BMD [47].

1.1.6. PET Scan

Comprehensive imaging of the entire joint, including soft tissues and bone, is made possible by PET/MRI systems, which is essential for researching intricate disease processes in osteoarthritis (OA). PET/MRI systems enable comprehensive imaging of the entire joint, including soft tissues and bone, which is crucial for studying complex disease processes in osteoarthritis (OA).In various joint tissues, PET/MRI can assess multiple early metabolic and morphologic markers of osteoarthritis (OA) concurrently. PET/MRI can evaluate several early metabolic and morphologic indicators of osteoarthritis (OA) simultaneously in different joint tissues [48]. Because molecular imaging may evaluate both molecular and pathophysiologic processes, it could be very helpful in the evaluation of musculoskeletal problems. This is especially true of PET/CT and PET/MRI. However, because of the high radiation dosages, discomfort experienced by patients, and low spatial resolution, its application is restricted. Additionally, standard PET scanners are not the best for tiny joints and tissues [49-50].

1.2. Pros and Cons of Imaging Techniques for Osteoarthritis Detection

Different imaging methods for diagnosing osteoarthritis that have several advantages, including the capacity to see joint damage and gauge the severity of the disease. Whereas MRIs provide fine-grained views of cartilage and soft tissues, X-rays provide unambiguous images of changes in the bone. Nevertheless, there are disadvantages to these methods as well. MRIs can be costly and difficult to obtain, and X-rays could not identify early cartilage loss. For osteoarthritis to be diagnosed and treated effectively, these benefits and drawbacks must be balanced. Major pros and cons of different imaging techniques for osteoarthritis are listed in Table 1.

Table 1. Pros & cons of different imaging techniques for diagnosing Osteoarthritis

Technique	Pros	Cons
Radiography (X-rays)	affordable, accessible, and easy interpretation	Limited ability to see soft tissues and radiation exposure
MRI	No radiation, precise imaging of cartilage and soft tissues	costly, time-consuming
Ultrasound	Real-time, affordable, non-invasive imaging	Restricted penetration and operator-dependent
CT	Thoroughly scanned bones, useful for subchondral abnormalities	exposure to radiation, reduced detail in soft tissues
DEXA	Beneficial for joint space constriction and bone density	Restricted application for seeing soft tissues
PET	Understanding of inflammation and metabolic activity	Radiation exposure, cost, and availability issues

Accurate disease prediction is essential for human health in the smart healthcare industry 5.0,

[51-52]. A smart healthcare system incorporates internet access to control a variety of cutting-edge equipment necessary for preserving and enhancing health. Using a network of gadgets including laptops, wearable technologies, and cellphones connected by the Internet of Medical Things (IoMT), people can

monitor and manage multiple aspects of their health with this networked method [53-56]. This integration is made possible in large part by IoMT, which establishes a seamless network that enables real-time data interchange between healthcare providers and devices [57]. These systems make it easier for people to monitor their health-related behaviors which promote general wellbeing and the early identification of possible health problems. These cutting-edge characteristics enhance everyday health management and stimulate continuous research and development to enhance and broaden the scope of intelligent healthcare solutions [58].

For medical practitioners, finding efficient treatments for chronic diseases [59], with intricate causes presents considerable difficulties. Electrocardiograms, laboratory test results, physical examinations, and other patient-related data can be collected in large quantities via cutting-edge technology such as wearable, mobile health applications [60], and other advanced medical instruments. To be valuable, this data must be effectively analyzed because it is frequently heterogeneous. To analyze and synthesize this complicated data and make better judgments, healthcare practitioners can make use of data mining and machine learning techniques [61]. The use of machine learning algorithms to comprehend socioeconomic characteristics and their influence on healthcare outcomes has expanded recently. People can now clearly perceive the tremendous prospects of integrating artificial intelligence (AI) with healthcare thanks to the growth of AI and the gradual initiation of AI research in the medical arena. Of them, the burgeoning subject of deep learning has demonstrated more promise in areas like medication response prediction and disease prediction [62]. One important part of the AI system utilized in healthcare is machine learning [63] The ubiquity of using ML is growing as a result of the healthcare industry's growing data volume [64]. With its roots in artificial neural networks, deep learning is a machine learning technique that has gained significant traction recently and holds the potential to revolutionize the field of artificial intelligence [65]. Deep learning techniques, particularly Deep Convolutional Neural Networks lessen the workload of medical practitioners by automating the diagnosis and classification of disorders [66].

CNNs are a common tool in artificial intelligence for image classification [67]. Before providing input, they go through flattening, maximum pooling, and data convolution. After going through several levels, the weights go into a back-propagation stage. A computer vision research topic called transfer learning uses a pre-trained model to learn from a dataset, which helps reduce the time-consuming nature of the training process. This method reduces generalization error and speeds up training. You can begin the training procedure with weights from earlier tiers and move to the new challenge as needed. When the first linked problem contains more labeled data than the problem of interest, this strategy works especially well.

Knee osteoarthritis (KOA) is a major medical condition marked by the gradual degradation of joint components, which results in pain and limited range of motion. It is impossible to overestimate the significance of early diagnosis as a significant healthcare concern. The incorporation of the Internet of Medical Things (IoMT) into Healthcare 5.0 [68] revolutionized patient care. Healthcare providers can identify early indicators of KOA and take prompt action thanks to the ease with which IoMT devices enable real-time monitoring and data collection. These systems can use pre-trained models to assess images of X-rays and increase predicted accuracy by employing transfer learning techniques. This helps speed up the diagnostic process and guarantee more accurate treatment options.

The use of cutting-edge technologies highlights the need of prompt diagnosis in the efficient management of KOA, with the ultimate goal of preventing additional joint damage and mitigating symptoms to enhance patient outcomes.

By employing transfer learning techniques on X-ray image data, the proposed study aims to advance early diagnosis and intervention procedures, ultimately leading to improved patient outcomes in the management of osteoarthritis.

- Deep machine learning is used in Healthcare 5.0 to predict chronic diseases, with a focus on classifying osteoarthritis as normal or osteoarthritic.
- The proposed IoMT-enabled deep machine model provides a more efficient and accurate method for chronic disease prediction.
- The suggested transfer learning approach leverages the foundational architecture of ResNet-18 and edge technology to enhance predictive capacity
- The model significantly improves the accuracy of predicting chronic osteoarthritis using deep machine learning approach by integrating multiple potential parameters in healthcare 5.0

- Experiments with real-world data demonstrate the importance of the proposed model and the effectiveness of the approach.

The structure of the paper is organized as follows: Section II reviews the latest advancements in osteoarthritis disease prediction as reported in the literature. Section III discusses the research methods and the proposed transfer learning (TL) model. & the dataset selection Section IV presents results and discussion. The conclusion and future work are covered in Section V, and the references are listed in Section VI.

2. Literature Review

Faster treatment and better healthcare services are now possible because to developments in healthcare technology, which have also led to the usage of electronic health records (EHRs), digital monitoring, and real-time information gathering. The integration of linked devices is made possible by the Internet of Medical Things (IoMT), which creates a network for processing real-time data and enabling efficient treatment procedures. The field of orthopedics has been profoundly impacted by IoMT because of the consequences of lifestyle choices and the rising rates of obesity, osteoporosis, and osteoarthritis. The potential of IoMT for better clinical care, better services, and efficient health monitoring for orthopedic patients is examined in [69] work.

An Errorless Data Fusion (EDF) technique was presented in this paper [70] to increase the precision of posture identification in smart healthcare applications. The study's foundation is a case study conducted in a medical facility. EDF is associated with the situational finding of patients by medical monitoring systems. To recognize problems in particular postures, it employs active and iterative learning. Regardless of user motions, this technique increases position detection accuracy, analysis length, and mistake rate. In patient care and therapy, wearable technology is essential, and the EDF approach is covered.

The number of senior people is rising, and early fall detection is essential to their well-being. In smart cities, automated fall detection through big data analytics is crucial. The study [71] suggest that, for intelligent big data analytics (IBDA)s, thermal imaging (TI) can be combined with machine vision. To identify falls in TI frames, a two-step deep learning algorithm is suggested. With an average inaccuracy of less than 3%, the system performs better than conventional fall detection techniques. Healthcare administration, real-time monitoring, and data processing are made easier by IoMT platforms. This effective plan offers senior citizens a secure and comfortable environment.

This [72] investigates the application of deep learning, more especially Convolutional Neural Networks, to the diagnosis of osteoarthritis in the knee. To categorize the incidence of knee osteoarthritis and segment knee structures, two 3D multi-task models are developed: OA_MTL and RES_MTL. With an accuracy score of 0.825 and a segmentation DSC score of 0.915, the models which employ an encoder-decoder architecture, residual modules, and depth wise separable convolutions perform better in classification tasks. The necessity for effective models in medical imaging is addressed by this method.

The study [73] investigates the influence of comorbidities on the advancement of osteoarthritis (OA) using claims data and electronic medical records (EMRs). The connected EMR-claims dataset from 2007 to 2014, which contains laboratory results, charges, and pain scores, is used in this investigation. To calculate the effects of major comorbidities on the course of OA, the researchers employed Cox proportional models and a relational dependency network technique. According to the study, integrating claims data with EMR can yield more precise sources of medical data.

In order to precisely identify osteoarthritis (OA), the author [74], presented a hybrid model that combines VGG16 with convolutional neural networks (CNN). Neural networks such as CNN, VGG16, VGG19, ResNet50, and CNN-ResNet are used in the model. The utilization of data augmentation strategies leads to improved accuracy in all models by mitigating the issue of class imbalance. Compared to existing state-of-the-art techniques, the suggested method (CNN-ResNet50) works better, yielding accurate results in all five phases of OA and obtaining an accuracy higher than 93% on training, validation, and testing datasets.

This work [75], suggests a deep neural network-based automated approach for classifying knee osteoarthritis. To enhance the texture of the tracercular bone, the knee X-ray images undergo pre-processing using frequency-domain filtering and histogram normalization. A two-step classification method is suggested, which uses the ResNet-50 network to categorize osteoarthritis grades and the VGG network to extract the joint center. To increase the effectiveness of iterative searches, a rapid search method and rebalance operation are also suggested. The classification accuracy of the approach is 81.41%.

The research [76] proposes an autonomous knee osteoarthritis severity measurement approach based on two deep convolutional neural networks (CNN). While the second network fine-tunes widely used CNN models to categorize knee joint images with a novel configurable ordinal loss, the first network recognizes knee joints in X-ray images with modest variability. Higher penalties are applied by the researchers to misclassification when there is a greater discrepancy between the anticipated and actual KL ratings. With a mean absolute error of 0.344 and an ideal classification accuracy of 69.7%, the updated VGG-19 model has a mean Jaccard index of 0.858 and a recall of 92.2%.

Convolutional neural networks (CNNs) were employed in [77]. In 2016 for classification. Their performance was significantly better than Wndchrm's. With an accuracy of 57.6% this research presents a novel approach utilizing deep convolutional neural networks to autonomously measure the degree of osteoarthritis in the knee using radiographs. The approach evaluates the severity using Kellgren & Lawrence (KL) ratings, a five-point rating system. The authors demonstrate how utilizing pre-trained models on ImageNet and fine-tuned on knee OA images can greatly enhance classification accuracy. They claimed that a better fit for assessing the precision of automated knee OA severity projections is a continuous distance-based evaluation metric such mean squared error.

The Deep Siamese Convolutional Neural Network has been used to build a new computer-aided diagnosis technique for osteoarthritis (OA) in the knee by the author in [78]. The Kellgren-Lawrence grading system is used by the approach to automatically rate the severity of OA. Three thousand patients were used to validate the approach, which was trained using data from the Multicenter Osteoarthritis Study. It obtained an average multiclass accuracy of 66.71% and a quadratic Kappa coefficient of 0.83. Additionally, an area under the ROC curve of 0.93 for radiological OA diagnosis was reported by the approach. It is thought that the model will help with both OA research and clinical decision making.

A machine learning model with multiple modes has been created to in [79] to forecast the advancement of osteoarthritis in the knee. The clinical exam findings, radiological data, and the patient's medical history are all incorporated into the model. The model, which was validated using 2,129 participants' 3,918 knee pictures, had an AP of 0.68 and an AUC of 0.79. By helping to create individualized treatment programs and enhance subject selection for OA drug-development trials, this might possibly save millions of joint replacement surgeries every year.

The author introduced a novel method for obtaining textural features associated with Osteoarthritis (OA) from radiographic knee X-ray images in [80], by means of complex network theory. Every pixel in the model is converted into a node, and Euclidean distance is used to connect two nodes. To eliminate edges and expose texture attributes, a series of thresholds is utilized. Knee X-ray pictures from the Osteoarthritis Initiative (OAI) database are utilized in a classification experiment to build a feature vector evaluated using a novel set of statistical measures. For the early identification of knee OA, the approach is both competitive and possibly promising.

EfficientNet-B0 architecture is employed in the [81], which is presented to increase the OA severity classification accuracy. 69.74% accuracy was obtained when this model was evaluated using a dataset that was made available to the public. This demonstrated the model's efficacy in more accurately determining the severity of OA, since it outperformed other contemporary techniques.

In [82], the severity of osteoarthritis (OA) was evaluated using X-ray images and the classical VGG-16 convolutional neural network (CNN) architecture in conjunction with transfer learning. To precisely identify the knee joint region, the pictures were preprocessed using a support vector machine (SVM) and the Sobel edge detection technique. The Osteoarthritis Initiative (OAI) provided 4,446 X-ray pictures for a total of 8,892 knees, which were used in the study. A 59.6% classification accuracy was obtained for the five Kellgren and Lawrence (KL) grades of OA severity.

The author [83] presents a novel method for automatically assessing the degree of osteoarthritis (OA) in the knee using X-ray images. The automatic localization of the knee joints and the subsequent classification of the localized knee joint pictures were the two primary processes in the process of automatically measuring the severity of osteoarthritis in the knee. To automatically identify knee joints, a fully convolutional neural network (FCN) is used. In order to measure the severity of knee OA, convolutional neural networks (CNNs) are trained from scratch by maximizing a weighted ratio of two loss functions: mean-squared error loss and category cross-entropy. This joint training naturally yields simultaneous multi-class classification and regression outputs and improves the assessment of knee OA severity.

This study [84], proposed a deep-learning algorithm for detecting knee osteoarthritis (KOA) using knee images after segmentation. The algorithm uses the Kellgren-Lawrence classification schemes and uses ResNet to segregate images. The Mendeley VI dataset was used for training, and cross-validation was performed on the Osteoarthritis Initiative dataset. The hybrid architecture overcomes imbalanced training data. The algorithm achieved a cross-validation accuracy of 78.57% and a testing accuracy of 84.09%. Transfer learning, a deep learning technique, accelerates training while decreasing generalization error. This method is more reliable and capable than current methods. Table 2 summarizes the methods and datasets presented in literature review section.

Table 2. Techniques and datasets presented in literature review

Ref	Method	Dataset
[72]	Multi-Task Neural Network	knee MRI scans (DESS) MRI
[73]	Logistic Regression Model	CMS and contained OA cases collected during 2007~2014
[74]	CNN	The dataset includes 1650 digital X-ray pictures of knee joints that were obtained from the hospital
[75]	Deep Neural Network	X-ray Dataset obtained from OAI Medical
[76]	CNN	Osteoarthritis Initiative (OAI) dataset
[77]	Deep Neural Network	dataset of X-ray images & KL grades obtained from the Osteoarthritis Initiative (OAI)
[78]	Deep Siamese Convolutional Neural Network	Data taken from the Multicenter Study of Osteoarthritis
[79]	Multimodal Machine Learning	metadata provided in the Osteoarthritis Initiative (OAI) and Multicenter Osteoarthritis Study (MOST) cohorts
[80]	AlexNet, VGG, GoogleNet, InceptionV3, ResNet, DenseNet and EfficientNet	Images from the OsteoArthritis Initiative (OAI) database showing the knee
[81]	EfficientNet-B0	Public Dataset
[82]	CNN	dataset of X-ray images and KL grades from the Osteoarthritis Initiative (OAI)
[83]	FCN	Osteoarthritis Initiative (OAI) Multicenter Osteoarthritis Study (MOST)
[84]	Deep Learning	Mendley VI dataset
Proposed Method	Transfer Learning, ResNet-18	Osteoarthritis Image dataset from Kaggle

3. Methodology

Chronic diseases are persistent conditions that impede an individual's quality of life and necessitate continuous medical care. Osteoarthritis is a frequent degenerative joint condition causing pain, stiffness, and decreased mobility, particularly in older adults. Early detection and treatment are vital to mitigate its symptoms. In this regard, Healthcare 5.0 leverages technologies like the Internet of Medical Things (IoMT) to provide sophisticated, individualized treatment. IoMT devices enable real-time health data collection and transmission, facilitating ongoing observation and early diagnosis. X-ray imaging is crucial for osteoarthritis diagnosis because it provides intricate images of bone and joint problems, allowing the identification of early disease symptoms.

3.1. Dataset

The X-ray images of knee joints used in the proposed method are taken from the publicly accessible Kaggle [85], collection and have been specially curated for the categorization of osteoarthritis. There are two main groups in the dataset: "Normal" and "Osteoarthritis." X-ray images of healthy knee joints free of osteoarthritis are included in the "Normal" category, whereas images displaying various degrees of osteoarthritic changes in the knee are included in the "Osteoarthritis" category. This dataset advances automated diagnosis of osteoarthritis by providing the basis for training and assessing the deep learning model intended to differentiate between normal and osteoarthritic states. Table 3 presents the number of instances of dataset utilized in the study and Figure 5 present the classes of the images of dataset under consideration.

Table 3. Number of instances of dataset

Osteoarthritis State	Number of Images
Normal	1589
Osteoarthritis	2247
Total	3836

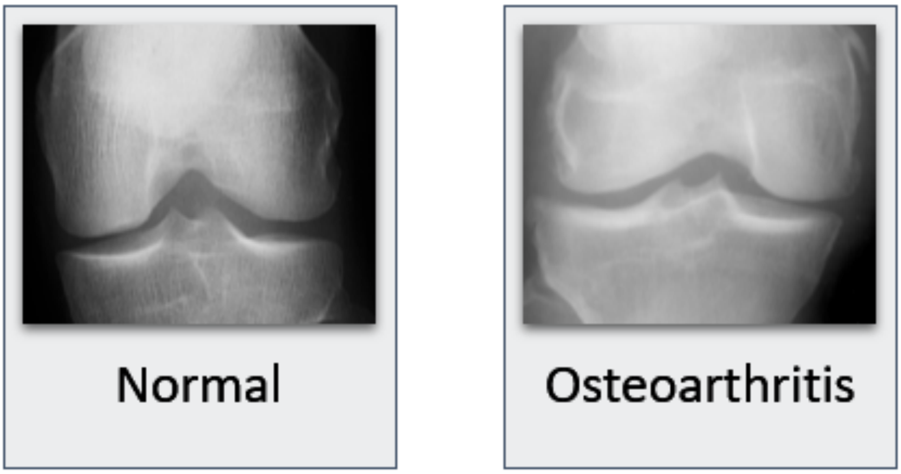

Figure 5. X-ray Images of dataset normal vs osteoarthritis

The proposed IoMT-enabled chronic osteoarthritis prediction system is shown in Figure 6 utilizes transfer learning to enhance the model's performance. Transfer learning involves using a pre-trained neural network model that has learned relevant features from large datasets to identify patterns in new, targeted datasets. This approach is particularly effective because it allows the model to swiftly adapt to classifying X-ray images of osteoarthritic and normal joints. The process begins with image acquisition. These images are preprocessed to enhance clarity, normalize contrast, and reduce noise, making them suitable for analysis. To make images from X-rays suitable for use in an osteoarthritis prediction model, preprocessing is done on them. The images are scaled during preprocessing to fit the model's input specifications. Furthermore, efforts are made to improve the quality of the images by eliminating any noise or artifacts that could impede precise analysis. In order to enable accurate and dependable predictions, these preprocessing steps are essential for making sure the images are well-prepared and standardized for input into the deep machine learning model.

The preprocessed images are then divided into training and validation datasets and fed into a transfer learning model. This model, based on pre-trained neural networks, is refined to classify the images into normal and osteoarthritic categories using the extensive information extracted from the X-ray images. Trained model is sent to cloud.

Transfer learning is integral to the proposed method because it leverages existing knowledge from extensive datasets, enabling quicker and more efficient model adaptation. By applying a pre-trained model, the system effectively distinguishes between normal and osteoarthritic conditions with limited data, saving time and resources while maintaining high accuracy. The trained model is stored at the edge layer, allowing for fast access. During the validation stage, the model's performance is evaluated to ensure it meets the required accuracy levels. If necessary, the model is retrained iteratively until optimal performance is achieved.

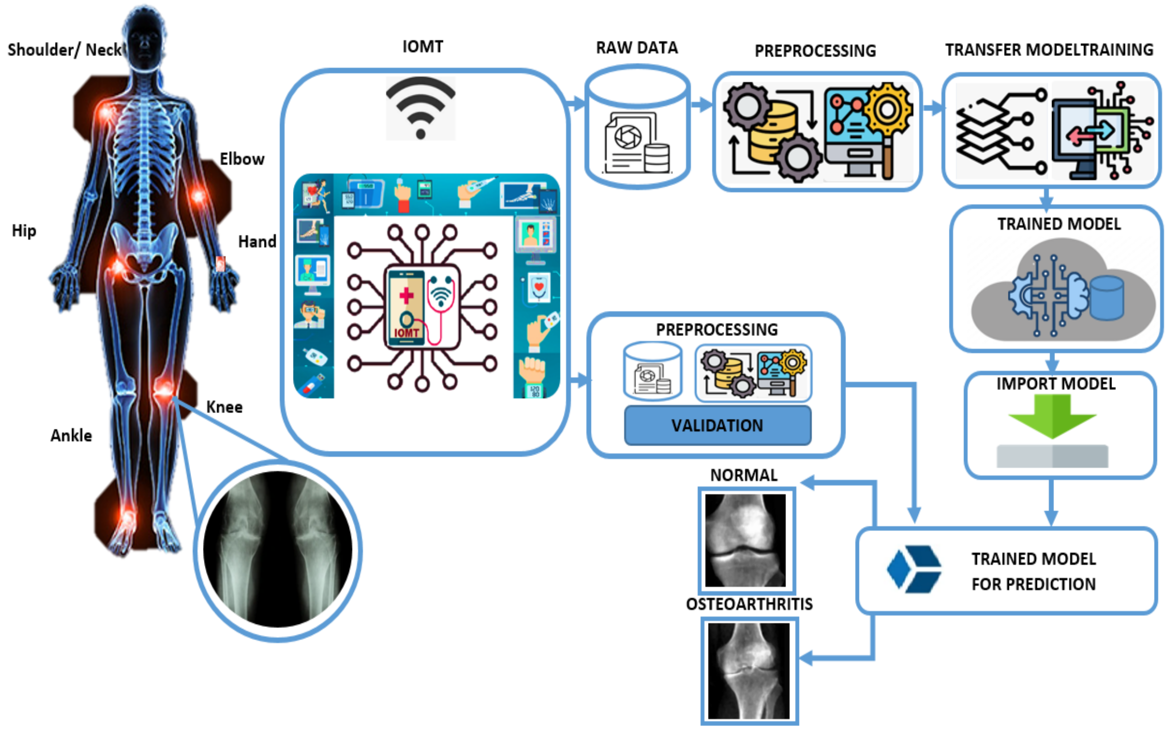

Figure 6. Proposed IoMT enabled model for chronic osteoarthritis Prediction

In methodology to predict osteoarthritis, we created a deep machine learning model for classifying knee X-ray images. The pipeline makes use of a well-liked convolutional neural network (CNN) model called ResNet-18 architecture. We modified the model, which was initially pre-trained on the ImageNet dataset, to enable binary classification that is, to discern between images with osteoarthritis and those without or normal.

To improve the generalization skills of the model, x-ray images are enlarged to 224x224 pixels and rotations, random horizontal flips, and color jitters, are applied to broaden the variety of training data. To ensure a uniform baseline for evaluation, the validation images are scaled and normalized without any enhancement. The architecture used by the model, ResNet-18, is renowned for its effective computational demands and robust performance in image classification. It is the foundation of this model because of its shown efficacy in image classification and its reasonable computational requirements. In order to create predictions for the two target classes relevant to the knee X-ray classification task, the fully connected (FC) layer of the architecture have been altered. Transfer learning have been utilized in this method, whereby a ResNet-18 model that had already been trained on ImageNet for this particular task have been optimized. We applied a pre-trained model to our customized dataset by utilizing its capacity to identify common features found in millions of images. Because convolutional layers are well-known for their capacity to recognize basic visual components like edges and textures, we kept the convolutional layers in place and trained with them unaltered.ResNet-18's fully connected (FC) layer is tuned to produce predictions for two classes normal and osteoarthritic specific to the job of classifying knee X-rays. Cross-entropy loss function, a popular option for classification tasks, is used for training, and an Adam optimizer with a 0.001 learning rate is used. A learning rate scheduler additionally fine-tunes the model, which is trained over 20 epochs with alternating training and validation periods, by reducing the rate of learning by a factor of 0.1 every seven epochs. To match the amount of output classes (normal and osteoarthritis) needed for this work, the FC layer in the last stage is been adjusted. This layer was only trained using the dataset we provided, which allowed the model to produce precise predictions that were suited to the knee X-ray categorization.

We investigated the possibility of integrating edge computing into our IoMT-based osteoarthritis prediction system to improve its effectiveness and efficiency. This method, which does computations close to the IoMT devices that gather the data, can greatly enhance data processing. Edge computing can result in predictions that are made more quickly and accurately by minimizing the need to transfer massive datasets to the cloud. Additionally, by reducing the transmission of sensitive information, local data processing enhances data security and privacy. Healthcare 5.0's guiding principles—better device interoperability and real-time decision-making—are supported by this idea. Even if our current system uses cloud-based processing, investigating edge technologies can provide insightful information on how future developments could maximize the efficacy and efficiency of our system.

By combining the capabilities of IoMT, X-ray imaging, and transfer learning within the framework of Healthcare 5.0, this system exemplifies how technology can revolutionize the management of chronic diseases like osteoarthritis, leading to improved patient outcomes and healthcare delivery.

4. Results and Discussion

The robust performance of the knee osteoarthritis classification model, constructed with the ResNet-18 architecture, was assessed over 20 epochs. The model demonstrated constant improvement during the training process, culminating in a remarkable overall training accuracy of 98.26%. This high training accuracy shows that the model successfully learned the complex information found in the knee X-ray images, making a precise distinction between osteoarthritic and normal conditions.

With an overall validation accuracy of 95.79%, the model showed a significant capacity for generalization in terms of validation. This high validation accuracy validates the model's robustness and dependability by showing that it can correctly categorize data that hasn't been seen. Overfitting is a typical problem in deep learning, and it appears that the model managed to avoid it based on the steady increase in both training and validation accuracies during the epochs. The reliable results on the validation set highlight the efficacy of the transfer learning strategy used, in which the ResNet-18 architecture which had been previously trained on the ImageNet dataset was optimized for this particular job. The model exhibits excellent potential for practical applications in predicting osteoarthritis from knee X-rays, as demonstrated by its high accuracies in both training and validation stages. This makes it a dependable tool for medical diagnosis and decision-making. Figure 7 depicts the accuracy curves of training and validation while Figure 8 presents the training and validation loss per epoch.

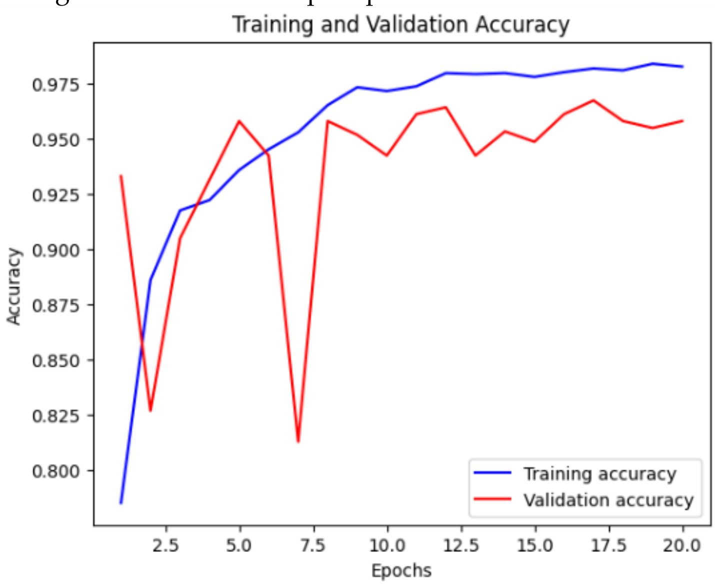

Figure 7. Accuracy curves for training and validation of the proposed model

4.1. Tools and Working Environment

Using Google Colab, the deep machine learning model for knee osteoarthritis prediction was put into practice and trained. This platform offered crucial computing resources for the model's development and assessment, with TensorFlow being used for training. Python 3.10.12 was installed, and the system included an Intel® CoreTM i7-7700HQ CPU which is operating at 2.80 GHz and 16 GB of RAM.

Table 4 summarizes additional training-related characteristics and preferences. These training configurations and parameters were identified as most effective in this study, having been validated across various conditions.

Figure 8. Loss curves for training and validation of the proposed model

Table 4. Parameters utilized in training

Training Parameter	Value
Size of Image	224x224 pixels
Total Number of Epochs	20
Iterations within Each Epoch	74 (training), 21 (validation)
Total Iterations	1480 (training), 420 (validation)
Starting Learning Rate	0.001
Learning Rate Scheduler	Reduces learning rate by a factor of 0.1 every 7 epochs
Execution Environment	Google Colab
Minibatch Size	32
Shuffle	Yes

4.2. Confusion Matrix

The confusion matrix gives information about the kinds of mistakes the model is making by showing the quantity of true positives, true negatives, false positives, and false negatives. Figure 9 represents confusion matrix of training data and Figure 10 depicts confusion matrix of validation data.

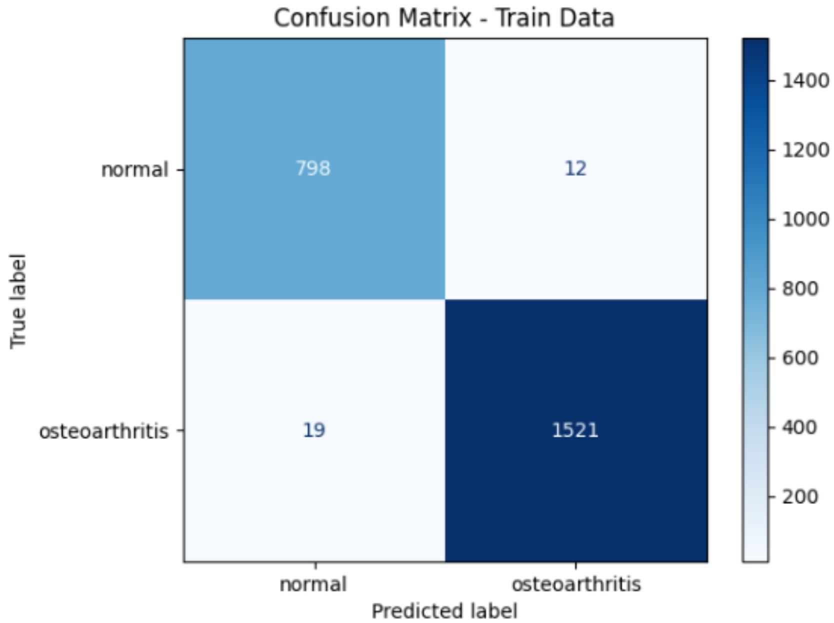

Figure 9. Confusion matrix of the training process of the proposed model

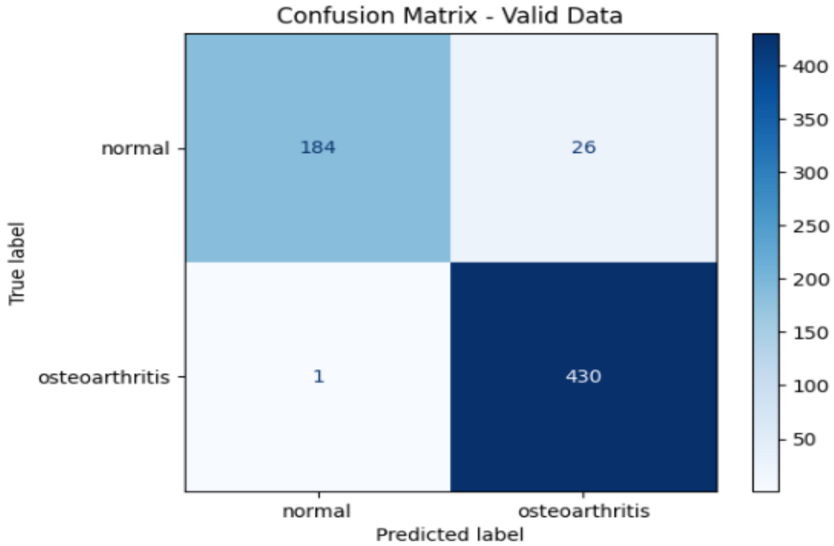

Figure 10. Confusion matrix of the validation process of the proposed model

The training data's confusion matrix offers a thorough analysis of the model's predictions. In this instance, 798 occurrences were effectively classified by the model as "Normal," indicating that they were true positives (TP), in which the model accurately detected the real "Normal" condition. In a similar, the model properly recognized the true "Osteoarthritis" condition in 1521 cases, equivalent to true negatives (TN) where the model correctly predicted the presence of the condition. Twelve cases were misclassified by the model, which indicated "Osteoarthritis" while it was "Normal." False positives (FP) are situations where the model mistakenly identified "Normal" cases as "Osteoarthritis." Furthermore, 19 occurrences were misclassified by the model as "Normal" when they were actually "Osteoarthritis." These are known as false negatives (FN), in which the model projected a "Normal" state in place of "Osteoarthritis" after failing to detect its presence.

The validation data's confusion matrix sheds light on how effectively the model distinguishes between "Normal" and "Osteoarthritis" conditions. Here, the model properly classified 184 occurrences as "Normal," which are true positives (TP)—that is, cases in which the model correctly detected the real "Normal" state. In this area, the model did, however, make 26 mistakes, accurately predicting "Osteoarthritis" rather than "Normal." False negatives (FN) are mistakes where the model misidentifies the "Normal" state and classifies it as "Osteoarthritis."

However, there were also very few false positives (FP) in the model; in just one case did it predict "Normal" when the true disease was "Osteoarthritis." In other words, the model mislabeled a case of "Osteoarthritis" as "Normal." In spite of this, the model performed admirably in accurately classifying 430 cases as "Osteoarthritis," which are true negatives (TN) in which the model effectively identified the true "Osteoarthritis" condition.

Overall, the matrix demonstrates how well the model classified most cases properly in both categories, but it also identifies areas where it might be improved in terms of lowering the proportion of false positives and false negatives. Table 5 provides the performance metrics of our proposed model.

Table 5. Performance metrics

Metric	Training Data (Normal)	Training Data (Osteoarthritis)	Validation Data (Normal)	Validation Data (Osteoarthritis)
Accuracy	98.26%	98.26%	95.79%	95.79%
Precision	98.53%	98.76%	87.41%	99.77%
Recall (Sensitivity)	97.67%	98.94%	99.19%	94.30%
Specificity	98.94%	97.67%	94.30%	87.41%
F1 Score	98.10%	98.85%	92.27%	96.85%

This system represents a substantial leap in the management of chronic osteoarthritis disease, enabling fast and accurate interventions that improve patient care. It does this by integrating IoMT, advanced imaging techniques, and transfer learning inside Healthcare 5.0.

The model performs well on a variety of criteria, according to the performance metrics for the training and validation datasets. With an astounding accuracy of 98.26% for the training dataset, the model correctly identified almost all cases. The precision of the model's predictions for each class, at 98.53% for "Normal" and 98.76% for "Osteoarthritis," indicates how reliable it is. The recall rates for "Normal" and "Osteoarthritis," respectively, are 97.67% and 98.94%, indicating that the model performs exceptionally well in recognizing the positive instances within each category. Specificity is 98.94% for "Normal" and 97.67% for "Osteoarthritis," indicating that the model is good at accurately differentiating between the classes. Taken together, these measures show that the model can reliably and accurately identify "Normal" and "Osteoarthritis" cases with low error rates. This strong performance on the training set is a sign of the model's efficacy and capacity for learning. Table 6 depicts a comparison table which shows the accuracy of different studies suggested by other researchers and our proposed method.

Table 6. Comparison of Accuracy across Various Research Studies with the Proposed Approach

Ref	Accuracy
[72]	0.82
[73]	Sensitivity 0.79 Specificity 0.83
[74]	93%
[75]	81.4%
[76]	69.7%
[77]	57.6%.
[78]	66.71%
[79]	Precision 0.68%
[80]	81.69%
[81]	69.74%
[82]	59.6%
[83]	61.9%
[84]	84.09
Proposed Method	**98.26% 95.79%**

To optimize chronic disease prediction in the context of Healthcare 5.0, deep machine learning integration is essential. The goal of Healthcare 5.0 is to improve patient care by utilizing cutting-edge technologies for real-time data processing and predictive analytics. The rapid advancement of cloud computing and connected devices has significantly influenced lifestyles worldwide, leading to a shift towards smarter modern infrastructure and objects [86].

By applying powerful al Modern infrastructure and objects are becoming smarter as a result of the rapid advancements in cloud computing and linked gadgets, which have had a huge impact on lifestyles throughout the globe.

Algorithms to evaluate large and complicated datasets, such as electronic health records and medical imaging, deep machine learning helps realize this ambition. By learning from vast amounts of historical and real-time data, methods like transfer learning and convolutional neural networks (CNNs) allow for accurate and timely predictions. Accurate disease prediction is made easier by this integration, which also improves patient outcomes by enabling prompt and tailored therapies. It also facilitates the smooth functioning of IoMT devices, which is consistent with Healthcare 5.0's focus on real-time decision-making and interoperability. Therefore, deep machine learning performs a pivotal role in propelling chronic disease management in the context of Healthcare 5.0, providing a revolutionary method for predictive healthcare. This paper highlights the potential of IoMT and Healthcare 5.0 in revolutionizing the management of this chronic disease by reviewing the epidemiological patterns, risk factors, histological features, pathophysiology, diagnostic tools, and therapy improvements for Osteoarthritis.

5. Conclusion

It is quite difficult to predict chronic diseases like osteoarthritis and treat patients in a timely and efficient manner. Osteoarthritis is a chronic disease that damages and affects the joints and lowers a person's quality of life dramatically. In order to solve this, we are creating an intelligent system for Healthcare 5.0 that is powered by IoMT and is intended to promptly and reliably predict osteoarthritis a chronic disease using deep machine learning.

In this work, utilizing transfer learning with a ResNet-18 architecture to create an IoMT-enabled osteoarthritis prediction system to achieve better accuracy and shorter response times, Our strategy integrates an IoMT-based approach with a transfer learning (TL) technique, utilizing a deep machine learning model to enhance chronic disease prediction. This combination leverages the strengths of IoMT for real-time data acquisition and transfer learning for improved model performance and accuracy. This combination makes prediction processing quick and extremely accurate. When the suggested system was simulated using the Healthcare 5.0 framework, it was able to the suggested system effectively distinguishes between knee X-ray images that are normal and those that are impacted by osteoarthritis utilizing the ResNet-18 architecture. With the help of the TL methodology, simulations of the IoMT-enabled intelligent system in Healthcare 5.0 obtained an accuracy rate of 98.26% for training and 95.79% validation, showing a notable improvement over earlier osteoarthritis prediction techniques. . This high accuracy highlights how well our method works to differentiate between osteoarthritis and normal circumstances, highlighting the model's potential for precise and timely diagnosis. Confusion matrices for training and validation datasets demonstrated the model's robustness and proficiency with real-world data.

This development supports the goal of Healthcare 5.0 by demonstrating the potential of fusing IoMT technology with deep learning models to improve chronic disease early diagnosis and management. Effective management of chronic diseases such as osteoarthritis necessitates early detection and ongoing monitoring. Patient-centered care objectives of Healthcare 5.0 can be aligned with the optimization of healthcare delivery and improvement of patient outcomes through the integration of machine learning with IoMT technology.

6. Future Work

We will investigate the integration of multi-modal data, including clinical records, patient demographics, and additional imaging modalities, to offer a more thorough assessment of osteoarthritis. In order to support Healthcare 5.0's holistic philosophy and improve forecast accuracy and dependability, we will integrate these many data sources.

Conflicts of Interest: "The authors declare no conflict of interest."

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