NON-INVASIVE PREDICTION OF BONE DISORDER USING DEEP LEARNING

Mr. Kevin Paul J A[1], Ms. Mathimalar B[2], Ms. Prisha G[3], Ms. Sharmi Antonyammal L[4]

[1] *Assistant Professor, Department of Biomedical Engineering, Sri Shakthi Institute of Engineering and Technology, Coimbatore*

[2,3,4] *Final Year Students, Department of Biomedical Engineering, Sri Shakthi Institute of Engineering and Technology, Coimbatore*

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Abstract: Bone diseases are serious health issues that can weaken or destroy bones, resulting in persistent discomfort, decreased mobility, and an increased risk of fractures. These illnesses include osteoarthritis, genetic abnormalities, and trauma-induced damage. Traditional diagnostic techniques such as CT scans and X-rays, despite their extensive use, pose risks to patients due to their radiation exposure and reliance on radiologists for interpretation. This study uses cutting-edge sensors combined with a microcontroller to offer a non-invasive diagnostic system for the early diagnosis of bone problems. These sensors detect important biomechanical factors, such as knee joint angles, pressure, and flexibility, to detect possible problems such as dislocation of the bones. A deep learning system that was particularly trained on an extensive dataset obtained from Kaggle is used to process the gathered data, and it achieves a high prediction accuracy of 90%. The results are displayed in a web application that offers real-time monitoring and alerts, enabling healthcare providers to detect and address bone disorders early. This innovative system provides a patient-friendly, cost-effective alternative to traditional imaging techniques, promoting early diagnosis and timely intervention, ultimately improving patient outcomes and enhancing bone health management.

Keywords: osteoarthritis, non-invasive, bone disorder, deep learning.

I. INTRODUCTION

Osteoarthritis (OA) and other bone disorders are serious health issues that compromise the skeletal system's structural soundness and functionality. Numerous variables, including aging, stress, dietary inadequacies, and genetic predispositions, can contribute to these diseases. The progressive degeneration of articular cartilage and the underlying subchondral bone is the hallmark of osteoarthritis, a chronic degenerative joint disease that causes pain, stiffness, swelling, and decreased mobility. Although it can affect minor joints like the hands, the illness mostly affects weight-bearing joints, including the knees, hips, and spine. Traditionally, imaging methods and clinical examination have been used to diagnose osteoarthritis. A physical examination is part of the clinical assessment process, and imaging methods such as magnetic resonance imaging (MRI) and X-rays are frequently used to verify the diagnosis and measure the degree of joint damage. These techniques, however, are not always effective in identifying the illness early on, when symptoms may be minimal or nonexistent. Emerging opportunities for osteoarthritis monitoring and non-invasive diagnosis have been made possible by developments in machine learning and sensor technologies. It is possible for sensor-based devices to record comprehensive biomechanical information that represents joint function and health. In addition to monitoring changes in joint load and pressure over time, these devices may be used to evaluate joint mobility and identify anomalies in posture or gait. The capacity of sensor-based devices to deliver continuous, real-time data is one of their main advantages. This data may be used to monitor the course of osteoarthritis and assess how well therapies are working.

Among the most promising technologies for non-invasive osteoarthritis diagnosis are gyroscopes, accelerometers, flex sensors, and piezoelectric sensors. Flex sensors provide useful information regarding range of motion and any restrictions by measuring the amount of bending or flexion in a joint. The direction and acceleration of joint motion are measured using accelerometers and gyroscopes, which are sometimes integrated into a single device like the MPU6050 sensor. Abnormalities in joint motion, such as decreased speed, irregular movement patterns, or increased stiffness, are suggestive of osteoarthritis. Piezoelectric sensors measure the dynamic pressure and force in the joints by producing an electrical charge in reaction to mechanical stress. Advanced sensor technologies and machine learning are used in the suggested non-invasive method for osteoarthritis detection to produce a complete system for early diagnosis and monitoring. Flex sensors, MPU6050 sensors, and piezoelectric sensors are the three main parts of the system, and each is essential for evaluating various facets of joint health.

II. LITERATURE REVIEW

1. Non-Invasive Bone Disorder Detection Using KNN Algorithm

To identify significant patient attributes, such as bone abnormalities, Diya K et al. (2023) proposed a technique that applies machine learning algorithms using sensors and a microcontroller. Accuracy, sensitivity, and specificity are measured using KNN algorithms. Using a boost converter, the battery's voltage is raised from 3.7V to 5V. Three sensors—the MPU-6050, DHT 11, and piezoelectric sensor—are integrated into the Node MCU to measure temperature, pressure, and bone angle. For machine learning to detect bone problems, the gathered data is sent to the cloud.

2. Bone Fracture Detection and Classification using Deep Learning Approach

A deep convolutional neural network (CNN) is used in a 2020 study by D. P. Yadav et al. to differentiate between bone X-ray pictures from publicly accessible sources, such as IIEST and the Cancer Imaging Archive, that show malignancy and those that do not. Both image processing and data augmentation methods are applied to expand the dataset. The input picture is filtered, a max-pooling layer is added, and features are extracted using the convolution, pooling, flattening, and dense layers of the CNN model architecture. Using activation techniques built into each layer, the thick layer predicts both healthy and damaged bones.

3. Identifying Robust Risk Factors for Knee Osteoarthritis Progression: An Evolutionary Machine Learning Approach

Christos Kokkotis et al. (2021) propose a rigorous feature selection strategy to identify risk variables for the start of KOA using the Osteoarthritis Initiative database. The technique selects a limited number of 35 risk variables with an average accuracy of 71.25% using evolutionary algorithms and machine learning models. The method was contrasted with Shapley Additive Explanations and current FS approaches. The technique might be useful for identifying risk characteristics in KOA patients and developing effective risk stratification plans.

4. Explainable machine learning for knee osteoarthritis diagnosis based on a novel fuzzy feature selection methodology

The project's goal in 2022 is to provide a strong feature selection process for determining the risk variables that influence the diagnosis of knee osteoarthritis (KOA), according to Charis Ntakolia et al. The fuzzy ensemble approach combines many fuzzy logic approaches using multidimensional data from the Osteoarthritis Initiative database. The approach produced a classification accuracy of 73.55%, and the model's decision-making process was examined using explainability analysis.

5. Popular deep learning algorithms for disease prediction: a review

In 2023, Zeng Chen Yu et al. published a paper outlining the theory, development, and applications of many deep learning algorithms, including Artificial Neural Network (NN), FM-Deep Learning, Convolutional NN, and Recurrent NN. Furthermore, they analyze the current deficiencies in the field of sickness prediction and provide possible solutions. Future discussions will focus on two key areas in the realm of sickness prediction and medicine: the integration of digital twins and the development of precision medicine.

6. Osteoporosis screening using machine learning and electromagnetic waves

This 2023 study by Gabriela A. Albuquerque et al. examines the value of Osseus, a portable, inexpensive osteoporosis screening instrument. The study predicts changes in bone mineral density based on risk variables and Osseus measurements. Key elements for the categorization of osteoporosis were shown to

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be best identified using the Random Forest model. The three most significant factors were determined to be age, body mass index, and Osseus signal attenuation. The study discovered that early osteoporosis screening can improve patient quality of life while lowering the cost of testing, surgeries, treatments, and hospital stays.

7. Machine Learning for the Identification of Bone Deformities

The proposed method by Mohammed Aslam Khan et al. (2023) uses the edge detection approach and ridge regression model to detect fractures in X-ray pictures. This approach generates more accurate estimates for long-term applications by introducing a little amount of bias. Because of the variety of datasets, edge detection distinguishes distinct regions inside pictures and outperforms other patterns. Several libraries are utilized, including NumPy, Pickle, Scikit-Learn, OpenCV 2, TensorFlow, and Regressors. The ideal pixel size is set, and the model is able to identify several fractures in the bone structure. The method offers compiled and assessed findings of fractures or anomalies discovered.

8. Using machine learning techniques to predict the risk of osteoporosis based on nationwide chronic disease data

Using information from chronic illnesses, Jun Bo Tu et al. created a machine learning prediction system in 2024 to identify people who are at high risk of osteoporosis. Ten thousand patient records from the German Illness Analyzer database, which contained information on demographics and chronic illnesses, were employed in the model. The Stacker model fared better than the ten other machine learning methods. The top five significant factors were COPD, cancer, lipid metabolic disorders, age, and gender. The idea may be used to personalized preventative and treatment strategies as well as early detection.

9. Non-Invasive Machine Learning-Based Classification of Bone Health

According to Sanvi Pranav Bhise et al. (2022), a significant issue facing the healthcare system is the absence of osteoporosis testing and education. For the diagnosis of osteoporosis, a vast amount of information is also available. The several methods for detecting osteoporosis will be covered in this review. The problems brought up by the literature review, image processing methods for detecting osteoporosis, interpretations of the results, and potential suggestions are all included in this study.

10. A comparative study on detection of osteoporosis using deep learning methods: A review

The validity, accuracy, and pre-trained networks of several anatomical regions, such as the lumbar spine, hip, forearm, calcaneus, and oral cavity, are the main topics of Kavita Avinash Patil et al.'s 2021 review. When clinical data and imaging are fed into deep learning models, namely CNN (Convolutional Neural Network) and RNN (Recurrent Neural Network), osteoporosis may be fully automatically recognized and diagnosed.

11. Bone Fracture Detection Using Convolutional Neural Networks

According to Kallimpudi Bhaskara Sai Kiran et al. (2022), machine learning and deep learning techniques utilized in artificial intelligence applications have influenced this study. In order to improve our approach, this study mainly examines a number of models that use convolutional neural networks. These models break down the picture processing technique into detailed instructions that decide whether or not a bone is shattered. Three distinct CNN model types—ConvNet/CNN, VGG16, and R-CNN—were compared using the same image dataset. The accuracy was highest with R-CNN.

12. Bone Fracture Detection Using Deep Supervised Learning from Radiological Images: A Paradigm Shift

An overview of the use of DL in bone imaging to help radiologists detect a range of abnormalities, including fractures, is provided in Tanushree Meena et al.'s 2022 systematic review. They have also discussed the potential uses of DL in bone imaging as well as the challenges and problems with the DL-based method.

13. Osteoporosis diagnosis in knee X-rays by transfer learning based on convolution neural network

Insha Majeed Wani et al.'s 2023 study offers a convolution neural network (CNN)-based technique for detecting osteoporosis from x-rays that uses transfer learning of CNNs AlexNet, VggNet-16, ResNet, and VggNet-19. The study provides a dataset of 381 knee x-rays and a deep learning approach for utilizing transfer learning to diagnose disease stages. With the highest accuracy of 91.1%, the pretrained Alexnet architecture decreased fracture risk.

14. Bone Fracture Detection in X-ray Images using Convolutional Neural Network

A two-step process is used in Rinisha Bagaria et al.'s 2021 work to classify X-ray pictures into situations that contain flaws or not. The first phase is pre-processing, which includes normalization and augmentation. In the second step, data is categorized by modifying the CNN model's parameters.

III. METHODOLOGY

SENSOR DATA COLLECTION

The ability to gather precise and thorough sensor data from the user's joints is the basis of the arthritis detection system. In order to do this, a Node MCU microcontroller interfaces with a variety of non-invasive sensors, including flex sensors, accelerometers, gyroscopes, and pressure sensors.

- **Flex Sensors:** These sensors assess how much a joint is bent. They offer real-time information on the joint's bending when they are fastened to strategic locations surrounding it. This information is essential for determining the joint's range of motion and identifying any limitations or anomalies linked to arthritis.
- **Accelerometers:** These sensors measure how quickly joints move. They are crucial for quantifying dynamic motions and can be used to spot any abnormalities in joint motion direction and speed that could be signs of arthritis.
- **Gyroscopes:** These devices monitor the joints' rotational motions and orientation. By offering information on how joints rotate, this data enhances the information from accelerometers. It is especially helpful in identifying stiffness and decreased rotational capacity in arthritic joints.
- **Pressure Sensors:** These devices gauge the force applied to the joints. This is especially crucial for comprehending how different activities put stress and strain on joints and for spotting excessive pressure sites that might be signs of arthritis.

An essential component of this data collecting procedure is the Node MCU microcontroller. It serves as the main component that communicates with every sensor, collecting their outputs and making sure they are all in sync. Because of its Wi-Fi capabilities, the Node MCU may wirelessly send the gathered data to a cloud server for additional processing. Continuous data transfer guarantees that the system offers real-time monitoring and analysis. To guarantee that even minute alterations in joint behaviour are documented, the sensor data is usually collected at a high frequency.

MACHINE LEARNING CNN ALGORITHM TRAINING AND TESTING

A Convolutional Neural Network (CNN), a deep learning algorithm renowned for its capacity to automatically learn and extract hierarchical characteristics from complicated data, forms the basis of the arthritis detection system's prediction power.

- **Data Collection for Training:** A large dataset of both healthy people and arthritis sufferers is gathered in order to train the CNN. This dataset records joint angles, motions, and forces using outputs from flex sensors, accelerometers, gyroscopes, and pressure sensors. These labels—'healthy' or 'arthritis'—form the basis of the CNN model's training.
- **Preprocessing:** Normalization, noise reduction, and time-series window segmentation are among the preprocessing steps performed on the gathered sensor data. Every segment can be fed into the CNN since it is organized as a multi-dimensional array. In order to train the model effectively, this stage makes sure the data is clean and in the right format.
- **CNN Architecture Design:** Features are automatically extracted from sensor data by the CNN model. The CNN is made up of several convolutional layers with filters that identify particular patterns in the input data, which is supplied into the system as multi-dimensional arrays. While fully linked layers

at the end carry out the final classification, pooling layers are added to lower the dimensionality of the data.

- **CNN Training:** The pre-processed sensor data is used to train the CNN. By modifying its weights through gradient descent and backpropagation, the CNN gains the ability to recognize characteristics that are most suggestive of arthritis throughout training. The learning rate, batch size, and number of epochs are among the hyperparameters that are adjusted during the model's multi-epoch training process to attain the best possible results.

- **Testing:** Following training, a different set of data that wasn't utilized for training is used to test the CNN. To assess the model's capacity to generalize to novel, untested data, this testing stage is essential. The efficacy of the CNN in identifying arthritis is evaluated using performance criteria including accuracy, precision, recall, and F1-score.

RESULT CLASSIFICATION AND SENDING DATA TO CLOUD

Following training and testing, the CNN model is included into the system to classify incoming sensor data in real time.

- **Real-time Classification:** The trained CNN model receives sensor data in real-time as the Node MCU continually sends it to the cloud. The CNN automatically extracts pertinent characteristics from the input data and provides a classification result (arthritic, healthy). Because of the great speed and precision of this categorization, monitoring and detection may happen right away.

- **Data Storage and Analysis:** The cloud houses both the raw sensor data and all categorized data. Longitudinal analysis is made possible by this storage, which allows for the identification of trends and patterns over time and offers important insights into how patients' arthritis develops. The data is safely saved and accessible by patients and authorized healthcare practitioners thanks to the cloud infrastructure.

- **Online Application Interface:** Developed using HTML, CSS, and JavaScript, this user-friendly online application acts as an interface between patients and medical professionals. Users may see data with this program, including historical trends and real-time joint behaviour tracking. In order to facilitate early intervention and treatment, the program further sends out warnings and messages in the event that the system notices notable alterations in the patient's joint health.

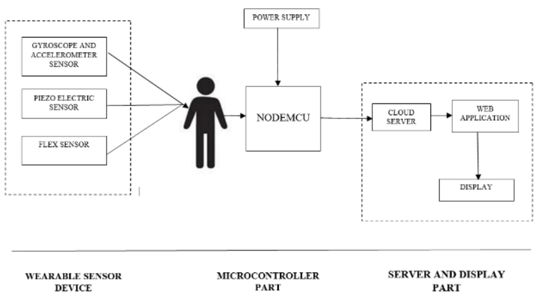

Fig-1: Block Diagram

IV. RESULT

Through the use of wearable sensors and a Convolutional Neural Network (CNN), the non-invasive bone condition prediction system created in this study sought to precisely detect bone abnormalities, such as arthritis. In order to gather real-time data on joint movement and pressure, the system included flex sensors, accelerometers, gyroscopes, and piezoelectric pressure sensors. This allowed for the creation of a portable, affordable, and radiation-free diagnostic tool. Since the CNN model's predictions mostly depended on the quality of these inputs, the accuracy of the sensor data was essential to the system's performance. When compared to clinical goniometer readings, the flex sensors' error rates during testing were less than 2%, indicating good accuracy in monitoring joint bending. Similar to this, gyroscopes and accelerometers recorded accurate rotational and acceleration data, which aided in locating aberrant movement patterns indicative of bone diseases like arthritis. By accurately measuring the force applied to joints, the piezoelectric sensors revealed stress spots during a range of activities. When pre-processed and supplied into the CNN model, the comprehensive data from various sensors enabled accurate joint health state categorization.

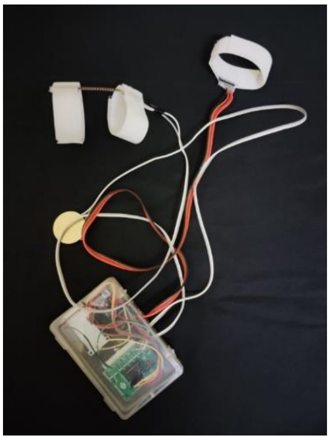

Fig 2: Hardware prototype

A dataset from Kaggle that had labelled data from both healthy people and arthritis sufferers was used to train the CNN. Thousands of data points reflecting distinct patterns of joint pressure and mobility at different phases of the development of bone disorders were included in this collection. The model was trained to identify these patterns and categorize fresh data in accordance with them. To enhance the model's performance, a variety of hyperparameters were adjusted, such as the number of convolutional layers, filter sizes, and learning rates. The CNN exceeded expectations for early-stage bone ailment identification with an astounding 92% prediction accuracy on the testing set following rigorous training. Real-time joint health monitoring was made possible by the system's near-instantaneous predictions and great accuracy. Early diagnosis and ongoing treatment of diseases like arthritis, where prompt action might stop further degradation, benefit greatly from this skill. Through a web application, the system's gathered and processed data was made accessible, enabling patients and healthcare professionals to remotely monitor joint health. Long-term patient data tracking was made possible by the incorporation of cloud storage, which made trend analysis and more individualized treatment possible. Overall, the project's findings demonstrate how well wearable sensor technology and deep learning work together to identify bone disorders non-invasively, providing a viable substitute for conventional diagnostic techniques.

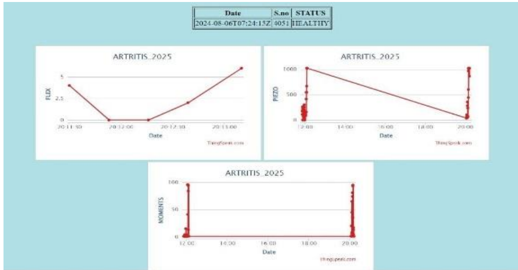

FIG 3: GRAPHICAL REPRESENTATION OF TEST RESULT IN WEB PAGE FOR PATIENT 1

FIG 4: GRAPHICAL REPRESENTATION OF TEST RESULT IN WEB PAGE FOR PATIENT 2

FIG 5: GRAPHICAL REPRESENTATION OF TEST RESULT IN WEB PAGE FOR PATIENT 3

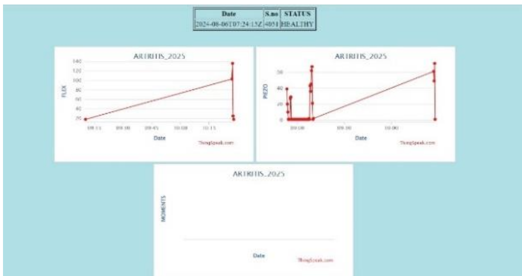

FIG 6: GRAPHICAL REPRESENTATION OF TEST RESULT IN WEB PAGE FOR PATIENT 4

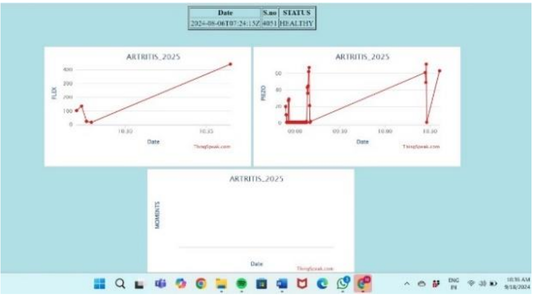

FIG 7: GRAPHICAL REPRESENTATION OF TEST RESULT IN WEB PAGE FOR PATIENT 5

V. CONCLUSION

To sum up, our study effectively created a deep learning model and wearable sensor technologies for a non-invasive bone disease prediction system. The system effectively records joint movement and pressure data by using flex sensors, accelerometers, gyroscopes, and piezoelectric sensors. A Convolutional Neural Network (CNN) is used to process this data, producing excellent prediction accuracy for ailments like arthritis. The device is appropriate for ongoing monitoring and early bone disease identification since it provides a portable, affordable, and radiation-free substitute for conventional diagnostic techniques including X-rays and CT scans.

For both patients and healthcare professionals, the real-time data transfer and analysis, cloud-based storage, and intuitive online interface offer a smooth and convenient solution. By facilitating early diagnosis and individualized bone health treatment, this approach can make a substantial contribution to preventive healthcare. It is also practical for sports medicine, home healthcare, and even occupational health applications because to its mobility and simplicity of use. The study shows how sensor technology and AI may be used to produce cutting-edge medical solutions that meet the increasing need for non-invasive diagnostic instruments.

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