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Using Convolutional Neural Network to Design and Predict the Forces and Kinematic Performance and External Rotation Moment of the Hip Joint in the Pelvis

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Abstract:- In order to improve the dynamic and kinematic adaptability of the hip joint, this paper presented a control attitude and kinematics and torque of the hip joint with power based neural network control. The CNN neural network uses input data only from the limb designed by the medical software, and is trained by different natural and artificially altered step patterns of healthy individuals. This type of network has been used for deep learning to realize adaptive speed control, dynamic and motion attitude, as well as prediction of force and torque performance. Detailed movement and torque tests were performed using MIMICS and ANATOMY AND PHYSIOLOGY software, and the obtained data were checked and varied by a healthy person, and finally, the test results showed that the neural network control system was able to control the selection. It has a variable and high speed with proper adaptation in various conditions. Finally, MATLAB software was used to design and predict the data of the problem, and favorable results were obtained.

Keywords:- *Kinematic and Dynamic Approach, Rotational Force and Torque, Medical Software, Anatomy, CNN Neural Network, Hip Joint in the Pelvis.*

I. INTRODUCTION

The pelvis is a crucial anatomical structure in the lower part of the body, governing various movements such as sitting and walking. Its significance lies in its role in positioning organs and systems, including the digestive and reproductive systems, as well as numerous muscles and veins. Additionally, the pelvis facilitates the transfer of body weight from the upper limbs to the lower limbs. The hip joint within the pelvis is particularly pivotal for movement and can be effectively analyzed and anticipated using various engineering and medical software.

Utilizing artificial neural networks and deep learning-based artificial intelligence, precise and relevant results and predictions can be derived from experimental data obtained from software or research articles. This has led to the acquisition of noteworthy findings and materials in related studies.

[1] To improve the diagnostic performance in detecting hip fractures on radiographs, deep convolutional neural networks (DCNN) were developed using computed tomography (CT) and magnetic resonance imaging (MRI) as a reference standard by radiologists. This enhancement was observed across all levels of reader experience. [2] We have created an automated deep learning system for the identification of hip fractures in frontal pelvic X-rays, a prevalent and significant radiological procedure. Our system underwent training using a decade's worth of clinical X-rays, totaling approximately 53,000 studies. It has the capability to be utilized with clinical data, effectively filtering out unsuitable and technically inadequate studies. [3] We have created an automated deep learning system for the identification of hip fractures in frontal pelvic X-rays, a prevalent and significant radiological procedure. Our system underwent training using a decade's worth of clinical X-rays, totaling approximately 53,000 studies. It has the capability to be utilized with clinical data, effectively filtering out unsuitable and technically inadequate studies. [4] A proposed computer-based classification system aims to categorize hips from pelvic radiographs as either normal or affected by osteoarthritis, and to differentiate between different levels of osteoarthritis severity. The study involved the evaluation of pelvic radiographs from 18 patients with confirmed unilateral hip osteoarthritis by three experienced physicians, who used the Kellgren and Lawrence scale to assess the severity of osteoarthritis as normal, mild/moderate, or severe. Various textural features, including five run-length, 75 Laws', and 5 novel features, were extracted from digitized radiographic images of the osteoarthritic and contralateral normal hip joint spaces of each patient. [5] With the rising volume of images per veterinary radiology study, there is an increasing demand for computer-assisted diagnostic methods. This study aimed to assess two machine-learning statistical models for the automated detection of image areas depicting the canine hip joint on ventrodorsal pelvis radiographs. [6] The prevalence of osteoarthritis is on the rise among the general population, primarily attributed to the aging population and a rise in obesity rates. A variety of imaging techniques are employed for the detection of hip osteoarthritis, with plain pelvic radiography being the initial and preferred method for diagnosis. [7] Developmental dysplasia of the hip (DDH) is

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a prevalent orthopedic condition in infants and young children. Precise identification and recognition of the distorted anatomical features are essential for diagnosing DDH. However, the variability in calcification and the deformities resulting from dislocation present challenges in accurately detecting misshapen pelvic landmarks for both human experts and computer systems. [8] Hip fracture is a significant global health concern among the elderly population. Failing to diagnose a hip fracture through radiography can result in a poor prognosis. The utilization of a deep convolutional neural network (DCNN) for processing radiographs has the potential to enhance the precision and effectiveness of hip fracture diagnosis. [9] Developmental dysplasia of the hip (DDH) is a condition characterized by abnormal development of the hip joint in infants. Precisely identifying the landmarks of the pelvis is essential for diagnosing DDH. Detecting the malformed landmark and diagnosing DDH is challenging for both human experts and computer systems due to the temporal variability and pathological deformity associated with the condition. [10] Publications on the application of machine learning in veterinary imaging are not common, but advancements in machine learning architecture and improved access to computing resources are expected to generate greater interest in this area. This study on diagnostic accuracy presents a specific type of machine learning, known as deep learning convolution neural network (ConvNet), for the detection and classification of hip dysplasia in ventro-dorsal (VD) pelvis radiographs used for hip dysplasia screening. [11] In total hip arthroplasty, the examination of postoperative medical images is crucial for assessing the success of the surgical procedure. Given the widespread use of Computed Tomography (CT) in orthopedic surgery, our study is centered on the analysis of CT images. Specifically, we are concentrating on the metal artifact present in postoperative CT scans, which is attributed to the metallic implant and can lead to decreased accuracy in segmentation, particularly in the proximity of the implant.

II. HIP JOINT IN THE PELVIS

The hip joint is a synovial joint with a ball-and-socket structure, comprising the femoral head and the acetabulum. It serves as the connection between the pelvis and the femur, linking the axial skeleton to the lower extremity. The hip joint, formed by the fusion of the ilium, ischium, and pubis, supports body weight and enables movement of the upper leg. The hip bone, or os coxae, is composed of the ilium, ischium, and pubis, and forms the bony pelvis along with the sacrum and coccyx. The hip joint connects the lower extremities to the axial skeleton, and the femur, the longest and heaviest bone in the human body, consists of a proximal end, shaft, and distal end. Movement in the hip joint occurs along three perpendicular axes, with the femoral head serving as the center. The transverse axis allows flexion and extension, the longitudinal axis permits internal and external rotation, and the sagittal axis enables abduction and adduction. Additionally, the hip joint supports weight-bearing and stability, which is influenced by factors such as the shape of the acetabulum, which can encompass the entire femoral head due to its depth.

- *Materials:*

The acetabulum is surrounded by a fibrocartilaginous collar known as the acetabular labrum, which serves several functions including load transmission, maintenance of negative pressure for enhanced hip joint stability, and regulation of synovial fluid hydrodynamic properties. The hip joint capsule is generally taut in extension and more relaxed in flexion. It comprises the iliofemoral ligament (Y ligament of Bigelow), pubofemoral ligament, and ischiofemoral ligament. The iliofemoral ligament, the strongest ligament in the body, attaches the anterior inferior iliac spine (AIIS) to the intertrochanteric crest of the femur. The pubofemoral ligament prevents excessive abduction and extension, while the ischiofemoral ligament prevents excessive extension, and the iliofemoral ligament prevents hyperextension. The ligamentum teres, located intracapsularly, attaches the apex of the cotyloid notch to the fovea of the femoral head and serves as a conduit for the foveal artery, which supplies the femoral head in infants and children. However, this vascular contribution to the femoral head blood supply is minimal in adults. Injuries to the ligamentum teres can occur in dislocations, leading to lesions of the foveal artery and subsequent osteonecrosis of the femoral head.

- *Muscles:*

The muscles of the hip joint can be categorized based on their roles in hip movements. Flexion is mainly carried out by the psoas major and iliacus, with some contribution from the pectineus, rectus femoris, and sartorius. Extension is primarily achieved through the gluteus maximus and hamstring muscles. Medial rotation is predominantly accomplished by the tensor fascia latae and fibers of the gluteus medius and minimus, while lateral rotation is primarily achieved by the obturator muscles, quadratus femoris, and gemelli, with support from the gluteus maximus, sartorius, and piriformis. Adduction is mainly performed by the adductor longus, brevis, and magnus, with assistance from the gracilis and pectineus. Abduction is primarily accomplished by the gluteus medius and minimus, with support from the tensor fascia latae and sartorius.

III. HUMAN ANATOMY MEDICAL AND ANALYTICAL SOFTWARE

In the world of science, various software are used for all kinds of applications. However, in this section, the explanation and review of the analysis software is discussed. By using the design and analysis of the anatomy of the organs, engineering and chemical analyzes can also be performed. First, by using the MIMICS software, MRI, CT SCAN, and FMRI images can be imported into the software in three cutting models. By means of these axial, coronal-sagittal cuts and applying load and finally kinematic, static and force calculations, you get the desired results. Finally, from the obtained results, different uses of analysis attack and predictions can be obtained using artificial neural network.

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In the second part, another software can be used similarly to check and validate the previous software activity. ANATOMY AND PHYSIOLOGY software is one of the three-dimensional software for analyzing the anatomy of the human body, which can be used to get a correct analysis if you are skilled in working with it.

In the third part, for experimental and mathematical-engineering analysis, ABAQUS software can be used to obtain detailed kinematic, dynamic, torque and force data, and at this stage, the accuracy of the results of the first part is proven, and the data can be confidently used for design. used neural network.

- *Data Information:*

In the first step for network design, the experimental data are completely categorized and to start the design process, they are classified into two categories: input data and target data. In this way, a simple mechanical model has been designed and simulated using software, and finally, the components that are considered for neural network design have been collected as two categories of information. 5 input data with the titles of rotational torque (angle) of the joint, dimensions of the joint (P, K) and 3 target data with the titles of force, kinematic and dynamic (P).

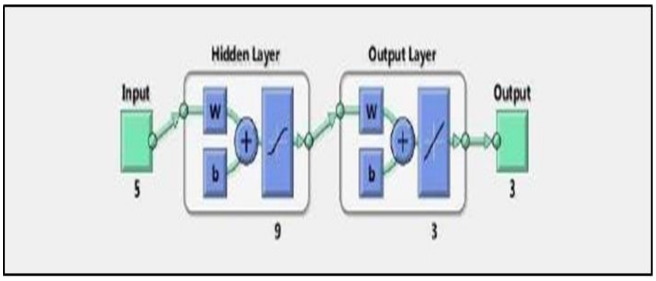

Fig 1 Schematic of CNN Neural Network with Input and Target Layer

IV. NEURAL NETWORK

In order to accurately analyze dynamic, kinematic, force, and rotational torque components and predict the performance of various systems, the use of neural networks is a suitable and efficient option. By utilizing recently extracted data, a neural network can be designed to estimate logical trends and assess the efficiency of the proposed system by comparing and analyzing results with historical samples. Throughout this process, results are thoroughly examined and analyzed using various tools, including software and mathematical analysis, to ensure comprehensive validation and enable confident continuation of the analysis. One recommended method for analysis and prediction is the application of artificial intelligence and neural networks.[13-19]

Neural networks are employed across diverse fields and are comprised of multiple layers and neurons. Each layer contains numerous nodes, where calculations are performed. Within each node, input data is multiplied by a weight, with the magnitude of the weight determining the data's impact. The sum of the data multiplied by their weights is then calculated, and this sum passes through an activation function to produce the output. As the number of layers and neurons increases, the model becomes more complex.[13-16]

Essentially, the neural network communicates through the numbers it generates, which are derived from the training data used to update the weights. For instance, in the context of banking, the network learns from observing various samples of previous customers and adjusting the weights accordingly. If it believes a person can repay a loan, it produces a number greater than 10 (which is converted to +50 with the activation function), and if it assesses that the person cannot repay the loan, it generates a number smaller than or equal to 10 (which is converted to -50 with the activation function).[12-17]

V. CNN NEURAL NETWORK

A Convolutional Neural Network (CNN) architecture comprises multiple stages or modules, each consisting of four primary elements: a filter bank known as a kernel, a convolution layer, a non-linear activation function, and an integration or subsampling layer. The objective of each stage is to represent features as a collection of arrays referred to as feature maps. Although most CNNs are created by combining basic linear and non-linear filtering operations, such as rectification, their implementation is not straightforward. [21-28] The filter bank or kernel is designed so that each filter or kernel aims to identify a specific characteristic at every input location. CNNs are utilized for classification or regression tasks. Convolutional neural networks encompass a significantly larger number of connections than weights. Furthermore, a convolutional network inherently offers a certain level of translation invariance. [22-25] This specific type of neural network assumes the desire to learn filters in a data-driven manner for the purpose of extracting features that describe the inputs. The inference presented is specific to two-dimensional data and complexity, but can be extended to an arbitrary number of dimensions without additional complexity. [23-27]

- *CNN Neural Network Modeling:*

The text provides an overview of the training process for the original AlexNet Convolutional Neural Network (CNN) and the application of transfer learning to convert it into an MsCNN capable of classifying powder bed anomalies. The original image was categorized using the K-MEANS clustering algorithm. The architecture of a CNN involves determining the number of layers for each type, as well as the size and quantity of filters for each layer. The design of the architecture is contingent upon the specific purpose of the CNN. Consequently, the learning rate is a crucial meta-parameter that should be established prior to commencing the training process. [22-24] It is important to note that a lower learning rate can yield more precise results, but may prolong the network training. The training dataset is typically divided into three subsets: the training set for network training, the validation set for model evaluation during training, and the test set for assessing the final trained

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model. Most CNN frameworks necessitate that all training data have uniform dimensions, thus data preprocessing is an initial step to normalize the data before the training process. [23-26] Transfer learning involves adapting a previously trained deep learning network to learn a new task. This approach is beneficial when creating new CNNs for each task and training the network from scratch is time-consuming. Instead, a pre-trained network can be utilized to learn new patterns, particularly when there is insufficient information to train the network. The concept involves freezing certain layers of a pre-trained network and typically adjusting the input and output layers. Various pre-trained models, including LeNet-5, AlexNet, VGG, GoogLeNet, and ResNet, are available for adoption. [22-25] The CNN training process employs back propagation. Initially, the weights of all kernels in a CNN are randomized. Each training round utilizes 70% of the images as the training set and the remaining 30% as the test set. The activation function in the training process employs Rectified Linear Unit (ReLU), which is superior to hyperbolic tangent (tanh). [22-28]

Table 1 Training Parametres

Parameters	Settings
MiniBatchSize	30
nitialLearnRate	0.0001
Hidden layer	9
Shuffle	Every-epoch
ValidationFrequency	30
ExecutionEnvironment	CPU

After designing the network as specified above, the following result was obtained in the regression diagram, which can indicate a very favorable and accurate result.

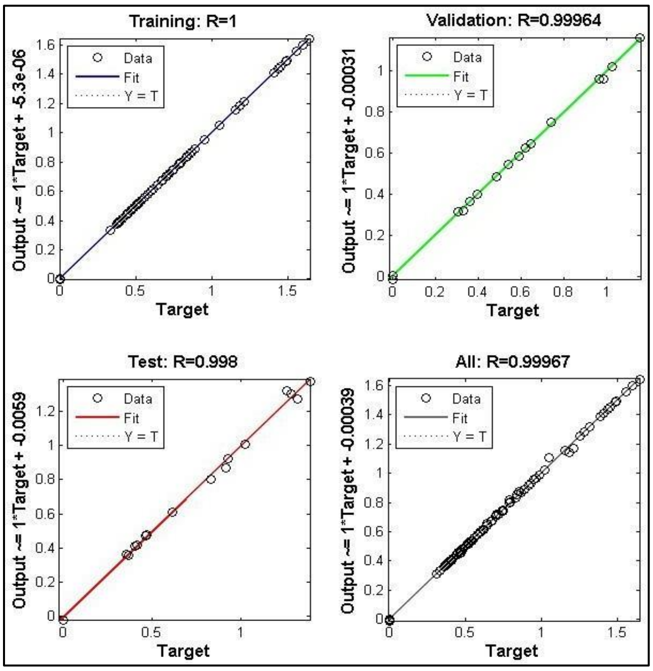

Fig 2 Neural Network Regression

The best result for linear regression is between 0.98 and 1, which can display high network accuracy in analysis.

VI. ANALYSIS AND REVIEW OF THE RESULTS

In this section, cinematic performance and force analysis and torque obtained from the neural network model are analyzed with the results of the experimental calculations compared. The results of calculations and analysis, which are calculated using control and evaluation relationships and based on theoretical and even empirical standards using MATLAB software, are presented in the table. In this study, the results are 0.99 to 1 for the number of hidden layers for the output parameters. In some certain circumstances this can be achieved and the desired result can be achieved. However, in this study, due to the high accuracy of the network type and deep learning, the results are very favorable due to the accuracy of the type of network design.

Table 2 Training Overall Result

Neural Network	Prediction
CNN	1

The results of the deep learning network are depicted in the figure. The ultimate findings demonstrate superior performance of the designed network in comparison to the experimental sample, accurately forecasting the final output data. The Mean Squared Error (MSE) and final regression outcomes are detailed in the pseudo-neural output section.

Table 3 Training Function

	Samples	MSE	R
Training	25	3559.29075e-0	1e-1
Validation	5	4294860.30898e-0	9.9999e-1
Testing	5	1853728.98074e-0	9.99980e-1

To further explore the influence and predictive capabilities of the network, it is necessary to analyze the final data from the regression diagrams using digital data graphing software and compare it with the findings of the experimental studies.

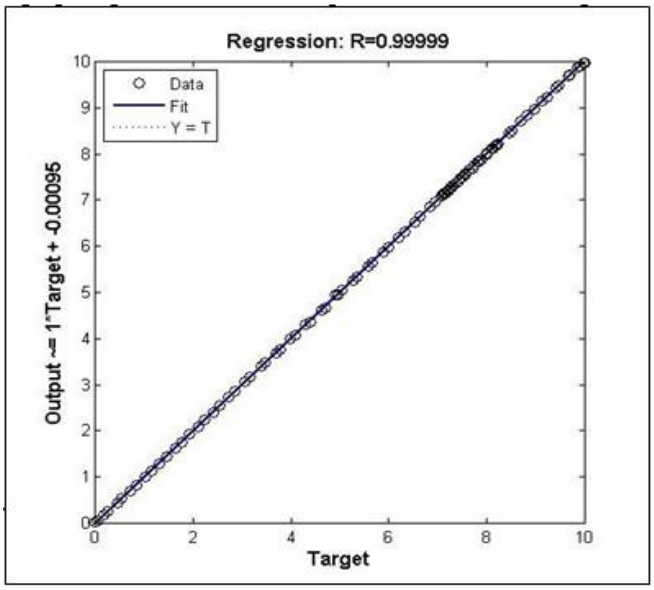

Fig 3 The Final Regression of the MLP Network

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The results show that the analysis has been performed with very high efficiency and the deep neural network has the highest efficiency for rotational, cinematic and voting function, one of the most important joints of the body.

VII. CONCLUSION

In this study, a straightforward model was developed and simulated using Mimics and Anatomy and Physiology. Experimental data was obtained and utilized to assess the accuracy of the model. ABAQUS software and approved literature were employed for simulation and design. Additionally, a neural network model was utilized in the deep learning process, and MATLAB software was used for network design. The findings were presented as a quadrilateral regression model. The accuracy of the neural network design and the resulting network models were numerically demonstrated in a table, highlighting the significance of predicting the variables in question. The primary objective of the study was to evaluate and predict the cinematic and dynamic behavior of the pelvic joint model in individuals under various conditions with high accuracy and under desirable circumstances.

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