Estimation of Knee Flexion Moment and Knee Flexion Angle of Multi-modal Data Using TransPose Architecture

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***Abstract*—The study of computational methods to predict Osteoarthritis with the Knee Flexion Moment are more active in the recent years. This project aims to propose the Deep learning model with method which uses TransPose model, which is Transformer application of Detecting Pose and it was implemented to reduce computational cost as this uses 6 sensors required to detect the pose of the leg which can challenge the state of the art model, OpenPose which uses 16 sensors are required for the similar experiment. The dataset used for the experiment is a Multi-modal data , which consists of IMU sensor data and the video data which Walking data from 14 subjects were recorded with eight IMUs and two smartphone cameras and the walking speeds consists of 3 different speeds 0.3,0.5,0.7 m/s. Through this project, the model has been able to detect the key points of the leg and was able to calculate the Knee Flexion Moment at every frame of the video data. More experiments should be performed to validate the result which was obtained through this project. We propose this model to use to analyze and visualize leg movements, estimate knee angles, and perform Biomechanical Analysis like Knee Flexion Moment based on the pose estimation results.**

***Index Terms*—Deep learning, Osteoarthritis, TransPose, Multi-modal data, IMU sensor data, Knee Flexion Moment, Pose Estimation, Biomechanical Analysis.**

I. INTRODUCTION

IN India Osteoarthritis is a very common disease it's also called degenerative joint disease, the cartilage, which serves as a barrier at the ends of bones, gradually deteriorates with time. The most typical symptom is joint discomfort in the hands, neck, lower back, knees, or hips. Medication, physical therapy, and occasionally surgery can help preserve joint mobility and lessen pain. really typical Over 10 million cases annually in India, although there is no cure for this illness, treatment can help. requires a diagnosis from a doctor Imaging or lab testing are frequently needed. Osteoarthritis has no known cure, but it also doesn't always get worse with time. It is thought that knee OA development and articular cartilage deterioration are facilitated by ambulatory knee joint loading [3]. As a surrogate measure of knee joint stress, the external knee adduction moment (KAM) is widely utilized. Medial compartment knee OA has been linked to a greater peak KAM during early stance, as well as to its existence, severity, and development [4–6]. A high external knee flexion moment (KFM) is associated with the deterioration of patellofemoral cartilage [8] and tibial cartilage [7], making it another important biomechanical test. Thus, it has been proposed that while evaluating joint loading, both KAM and KFM should be taken into account [9].

Force plates and optical motion capture systems are pricy pieces of equipment often found only in research labs and highly specialized clinics, and they are used in the measurement of KAM and KFM. As a result, the majority of patients and medical professionals lack access to instruments for routine joint kinetics examination. Clinical care may be more effectively provided to patients and less time spent in gait laboratories if portable gait assessment technologies were available for use in clinics or at home. For instance, the prescription of gait training programs [10], [11] may be applied to homes or clinics.

Inertial measurement units (IMUs), which enable lightweight and low-cost sensing, now present a new opportunity for estimation of kinetics in natural environments when combined with musculoskeletal or machine learning models. Musculoskeletal models first optimize the body kinematics, muscle forces, and ground reaction forces based on data from IMU sensors placed at major body segments [12]– [14]. Then, the knee moments are computed by solving optimal control problems [12] or computed from ground reaction forces using inverse dynamics [13], [14]. A musculoskeletal model can provide comprehensive lower extremity gait analysis, but many error sources—including reduced degrees of freedom, simplified muscle properties, and inaccurate foot-ground contact modelling—make it difficult for it to reduce the noise and drift present in the IMU data [12]– [14].

In contrast, machine learning models directly map IMU data to knee moments using experimentally collected training data, making them less likely to suffer from integration drift. Different neural network variants have been implemented to estimate knee moments from one to five IMUs [15]– [18]. The rationale for using machine learning is that the inertial data contain adequate information for knee moment estimation.

Robust tracking of anatomical keypoints (e.g., hip, knee, and ankles) from 2-D movies captured in natural contexts, including smartphone videos, is made possible by new human body key point (joint center) identification algorithms [19]. In a simulation experiment, where 3-D marker trajectories recorded by optical motion capture were projected onto 2-D planes to simulate camera-based keypoint recognition, the identified keypoints demonstrated potential for knee moment estimation. When random noise was added to the simulated keypoints to simulate real video-derived data, the accuracy

Parameters of IMU and Smartphone Camera

	IMU	Smartphone camera
Module	SageMotion	Apple iPhone 11
Sampling Rate	100 Hz	120 Hz
Number of Nodes	8	2
Weight per Node	43 g	194 g
Size per Node	58 × 38 × 19 mm	151× 76 × 8 mm
Resolution	0.1 mm/s^2, 0.06 °/s	1920 × 1080 pixels
Position	Trunk, pelvis, and both thighs, shanks, and feet	Back and right side of the subject

Fig. 1. Parameters of IMU and Smartphone Camera

significantly dropped, suggesting that current keypoint detection algorithms might not be accurate enough for knee moment estimation based solely on cameras. However, promising results were obtained when no noise was added to the simulated keypoints. Fusion of data from IMUs and cameras has enabled more accurate estimation of kinematics in computer vision applications, since the segment pose information from the cameras can partially compensate for the drift present in IMU-based approaches. It is unclear if the combination of these two sensing modalities can enhance joint kinetics estimates, even if they are complimentary.

We present here a TransPose model that suggested to estimate Knee Flexion Moment (KFM) during walking from a fusion of IMUs and smartphone video data [1], to build a robust model for various walking conditions, different gait modifications were tested, including changes in walking speed, trunk sway angle, foot progression angle, and step width. The improvement in accuracy from sensor fusion was evaluated by comparing models using both IMUs and cameras, IMUs alone, and cameras alone. Knee Flexion Moment (KFM) estimation accuracies compared to either IMUs alone or cameras alone by clinically meaningful margins. We also hypothesized that more IMUs would lead to higher KFM estimation accuracy.

II. Methods

A. Dataset

To engage in this work, seventeen subjects (all male; age: 23.2 ± 1.1; height: 1.76 ± 0.06m; mass: 67.3 ± 8.3kg; BMI: 21.5 ± 2.1kg/m2) who had no prior history of musculoskeletal diseases participated. Before being tested, each patient gave written informed consent, and the Institutional Review Board examined and approved the experimental protocol.

In this study, researchers explored how different walking conditions affect human gait by using a mix of advanced motion capture technology, IMU sensors, and smartphone cameras. They started by placing reflective markers on 32 key points of each participant's body, including areas like the heel, various points on the feet, ankles, knees, shins, hips, and several points along the trunk and shoulders. These markers' movements were captured at a rate of 100 times per second using a ten-camera system from Vicon, providing a detailed map of how each part of the body moved during walking.

Ground reaction forces, which are the forces exerted by the ground on the feet during walking, were measured at a higher rate of 1000 times per second using an instrumented treadmill from Bertec Corporation. This high-frequency data collection allowed for precise analysis of how the feet interact with the ground.

Eight Inertial Measurement Units (IMUs) from Sage Motion, each capable of real-time calibration, were attached to different parts of each participant's body, including the trunk, pelvis, thighs, shins, and feet. These sensors, recording data at 100 times per second, were carefully aligned to follow a standard coordinate system.

To capture visual information, two iPhone 11 cameras were set up: one behind and one to the right of each participant. These cameras recorded at 120 times per second, providing clear views of the movements from the back and the side. Each camera was positioned 3 meters away from the center of the treadmill and 1.2 meters above the ground.

The experimental procedure began with each participant walking at their preferred speed for two minutes to establish a baseline. This baseline helped determine each person's normal foot progression angle and step width, which were used as reference points for later trials.

After establishing the baseline, participants performed three types of gait modification trials: adjusting foot progression angles, step widths, and trunk sway angles. Each trial combined three different walking speeds (preferred speed, 0.2 meters per second slower, and 0.2 meters per second faster) with three variations of the specific parameter being tested. For instance, in the foot progression angle trial, the angles tested were the baseline angle, 15 degrees less than the baseline, and 15 degrees more than the baseline. Similar variations were used for step widths and trunk sway angles.

Each trial lasted 4.5 minutes, with each combination of speed and parameter variation being tested for 30 seconds. The order of these tests was randomized to prevent any learning effects. Participants received real-time visual feedback from a monitor in front of the treadmill, helping them adjust their walking patterns as needed.

Before each set of gait modification trials, participants practiced the required changes to ensure they could follow the visual feedback correctly. This practice helped reduce any differences between what was intended and what was actually performed. Additionally, before starting each trial, participants stood on one foot and swung the other leg three times to ensure the data from different sensors and cameras were perfectly synchronized.

B. Data Processing

1) Ground-Truth Knee Flexion Moment (KFM): A zero-lag fourth-order Butterworth filter was used to low-pass filter marker data and force plate data at a frequency of 15 Hz. Since data analyses were done on each subject's right knee, only the appropriate steps were taken in this investigation. The ground-truth right stance phase was identified using a threshold of 20 N in the vertical ground response force. The ground-truth right knee moments were determined using the cross-product approach based on marker and force plate data

2) 2-D Joints from videos: TransPose: Keypoint Localization via Transformer [1], in this research the authors proposed a model called TransPose, which introduces Transformer for human pose estimation. The attention layers built in Transformer enable their model to capture long-range relationships efficiently and also can reveal what dependencies the predicted keypoints rely on. To predict keypoint heatmaps, the last attention layer acts as an aggregator, which collects contributions from image clues and forms maximum positions of keypoints. The zero-lag second-order Butterworth filter was applied at 15 Hz to filter the interpolated 2-D joint positions. To match the IMUs' sampling rate, the filtered 2-D joint locations were down-sampled from 120 to 100 Hz by linear interpolation. The origin was determined as the midpoint of the left and right hip joints, ensuring that additional 2-D joint placements were not dependent on the subject's location within the global frame. To lessen the impact of subject size, BH normalized the 2-D joint locations.

3) Data Synchronization: Data and optical motion capture data were utilized to separately calculate the magnitude of right shank angular velocity during the three swings prior to each trial. The two data sources were then synchronized using the results of a cross-correlation. Using the same technique, the camera and optical motion capture data were synchronized by matching the right shank angle. The conclusion goes here.

III. Proposed Deep Learning Model

Deep learning models are very capable to detect the pose and estimate the pose, OpenPose (version 1.7.0, Body_25 model) [19], a joint center detection algorithm, it used to estimate the 2-D positions of the shoulder, hip, knee, and ankle joints from each frame of the video and geometry- and physics-based approaches are used to extract biomechanical parameters, and recurrent neural network (RNN) encoders are used to extract features from acceleration, angular velocity, and 2-D joints [2]. Continuous data are first divided into discrete steps of varying durations. Second, recurrent neural network (RNN) encoders are utilized to extract features from acceleration, angular velocity, and 2-D joints, and geometry- and physics-based techniques are used to extract biomechanical parameters for each step. Third, one of the multimodal fusion techniques is employed to fuse the features that the RNN encoders extracted. In order to estimate KAM and KFM, the fusion output and the biomechanical parameters are finally concatenated and input into a fully connected network.

Our suggested deep learning framework estimates the knee flexion angle (KFA) while walking by utilizing state-of-the-art computer vision and sequence modelling approaches. We utilize the most advanced object detection model available, Faster R-CNN, to locate and recognize wearable sensors inside video frames. Then, 2D human pose estimation from the video data is achieved by using the TransPose model [1], which is based on the robust Transformer architecture. We provide a unique Transformer-based method that learns long-range relationships in the video sequences to further increase the accuracy of posture estimate. We use a Transformer encoder to extract complex temporal patterns from the inertial

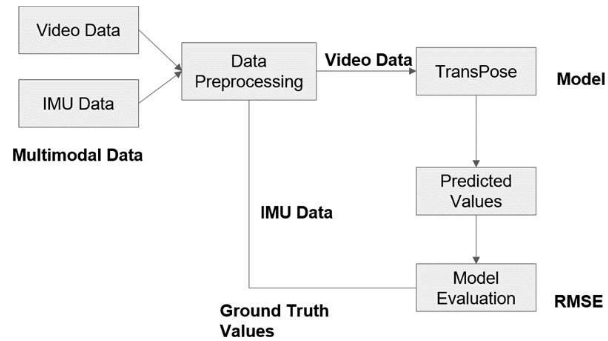

Fig. 2. Methodology diagram

measurement unit (IMU) data streams in parallel, which can help with KFA estimation. Through strategic fusion of information from vision and sensing modalities, our unified deep learning pipeline generates precise KFA predictions, enabling comprehensive gait analysis and biomechanical assessments.

The goal of the proposed deep learning model is to use computer vision techniques to evaluate human gait patterns and predict biometric parameters, like knee adduction angle. The algorithm processes depth pictures taken from different angles by using pre-trained object detection and posture estimation models. To improve comprehension of the depth information, Initially, the depth frames are converted into visually interpretable coloured images, facilitating better understanding of the depth information. The images are then put through preprocessing procedures like normalization and scaling to make sure the pre-trained models work with them. While the posture estimation model is used to locate and identify important anatomical landmarks like joints and limb segments, the object identification model is used to identify regions of interest within the images. After these landmarks are identified, the pertinent keypoints pertaining to the hip, knee, and ankle joints of the lower limbs are extracted by processing.

By employing vector algebra operations and geometric calculations, the model computes the knee adduction angle, a crucial metric in biomechanics and clinical settings. This angle provides insights into the alignment of the lower limbs and can aid in the identification of potential risk factors for knee injuries or conditions like knee osteoarthritis. The estimated knee adduction angle, along with other relevant data, is stored and subsequently visualized through interactive plots. These visualizations depict the temporal evolution of the keypoint coordinates, enabling researchers and clinicians to analyse gait patterns, identify anomalies, and potentially develop interventions or rehabilitation programs tailored to individual needs.

The deep learning model's versatility lies in its ability to process depth images from various viewpoints, allowing for a comprehensive analysis of gait patterns. Additionally, the modular design of the model facilitates the integration of additional functionalities, such as joint angle calculations or gait cycle segmentation, by leveraging the extracted keypoints and anatomical landmarks. All things considered, the

$$\text{Knee Flexion Moment} = \text{body mass} \times g \times \text{thigh length} \times \sin(\theta)$$

Equation for KFM

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

Equation for RMSE

suggested deep learning model is an effective tool for non-invasive gait analysis, filling the gap between biomechanical evaluations and computer vision methods. This approach has the potential to change the area of gait analysis by enabling precise visualizations and accurate calculation of biometric data. This could lead to individualized therapies and improved patient outcomes. We analysed performance indicators like The Root Mean Squared Error (RMSE) between the ground truth values that we considered as Inertial Measurement Units (IMUs), That is Eight IMU sensors with built-in real-time calibration (SageMotion, Kalispell, MT, USA) (sampling rate: 100 Hz) data that collected from each subject. We considering that that will be the high accurate data that can me compared with the model predicted values.

IV. Performance Measures

This model detects the keypoint of the video data, which was divided into frames, and the data points predicted are comtinuous 2 –d arrays , so Root Mean Square Error should be calculated to verify the model's accuracy. In order to assess the accuracy of the TransPose model in recognizing leg keypoints in video frames, we choose the Root Mean Square Error (RMSE) as the main statistical measure. Root Mean Square Error (RMSE) is a commonly employed metric for assessing the precision of models in forecasting continuous variables. The measure calculates the square root of the average of the squared discrepancies between expected and observed values. This statistic offers a precise assessment of the model's performance in respect to the magnitude of the errors. The equation represents the relationship between the actual value (actual), the predicted value (predicted), and the number of observations (N). RMSE is utilized to measure the discrepancy between the coordinates of the anticipated keypoints and the actual keypoints. Smaller RMSE values indicate higher accuracy.Accurate and reliable data is essential for computing the root mean square error (RMSE) for the video frames. This file contains the precise coordinates of the notable features for each frame. Usually, these keypoints are labeled manually and serve as the reference points for evaluating correctness. For this project we have used the Groud truth values as the sensor data.

The TransPose model has successfully detected the prominent locations for each frame. Computation of the root mean square error (RMSE) for every each frame: Calculate the Root

Fig. 3. Predicted keypoints

Mean Square Error (RMSE) by comparing the anticipated keypoints with the actual keypoints for each frame. Determine the cumulative Root Mean Square Error (RMSE) for the video series by aggregating this data.

V. Results and Discussion

The TransPose model effectively utilized pre-trained weights to precisely detect leg keypoints across video frames. Keypoints were determined for every frame, enabling the computation of knee adduction angles and the accompanying knee flexion moments. The chosen keypoints provide a significant level of reliability in accurately identifying important leg joints, therefore facilitating the subsequent calculations of angles and moments.

The knee adduction angles varied between 22.17 degrees and 173.66 degrees during the first 10 frames, indicating that the model accurately represents a broad spectrum of actions. Nevertheless, a limited number of frames yielded a 'nan' value for both knee adduction angles and knee flexion moments, suggesting either difficulties in finding keypoints or inaccuracies in the computations for those frames. More specifically, anomalies were identified in frames 5, 8, 9, and subsequent frames, highlighting the necessity for more improvements in the model or preprocessing techniques.

The knee flexion moments exhibited significant variability, with measurements of 260.58 Nm for frame 1, 134.66 Nm for frame 2, and 103.64 Nm for frame 3. The observed fluctuations demonstrate the dynamic nature of knee movement during the recorded activities. The presence of 'nan' values in knee flexion moments was shown to be linked to the frames in which knee adduction angles were likewise 'nan'. Indications point to the fact that the lack of certain data directly influenced the calculation of the knee flexion moment.

The findings suggest that the TransPose model is proficient in conducting biomechanical research. However, they also stress the need for enhancements, specifically in dealing with situations when the identification of keypoints may not succeed or yield less trustworthy outcomes. The computed knee angles and moments offer a clear and valuable comprehension of the knee's mechanics, which are beneficial for application in sports science, rehabilitation, and orthopedics. Additional efforts are required to tackle the existence of 'nan' values and improve the reliability of the model's predictions over all frames. To validate the results obtained, further experiments should be performed to obtain the Knee Flexion Moment ground truth values.

```
Frame 1: Knee Adduction Angle: 108.43494882292202 degrees
Frame 2: Knee Adduction Angle: 150.64224645720873 degrees
Frame 3: Knee Adduction Angle: 22.166345822082455 degrees
Frame 4: Knee Adduction Angle: 173.65980825409005 degrees
Frame 5: Knee Adduction Angle: nan degrees
Frame 6: Knee Adduction Angle: 49.02199017702011 degrees
Frame 7: Knee Adduction Angle: 146.30993247402023 degrees
Frame 8: Knee Adduction Angle: nan degrees
Frame 9: Knee Adduction Angle: nan degrees
Frame 10: Knee Adduction Angle: 158.96248897457818 degrees
Frame 11: Knee Adduction Angle: nan degrees
Frame 12: Knee Adduction Angle: 1.8603909437914135 degrees
Frame 13: Knee Adduction Angle: 18.434948822922017 degrees
Frame 14: Knee Adduction Angle: nan degrees
Frame 15: Knee Adduction Angle: 0.0 degrees
Frame 16: Knee Adduction Angle: nan degrees
Frame 17: Knee Adduction Angle: 26.565051177077994 degrees
Frame 18: Knee Adduction Angle: nan degrees
Frame 19: Knee Adduction Angle: nan degrees
Frame 20: Knee Adduction Angle: nan degrees
Frame 21: Knee Adduction Angle: nan degrees
Frame 22: Knee Adduction Angle: 126.86989764584402 degrees
Frame 23: Knee Adduction Angle: nan degrees
Frame 24: Knee Adduction Angle: nan degrees
Frame 25: Knee Adduction Angle: 73.55962047831983 degrees
Frame 26: Knee Adduction Angle: 107.8297342256772 degrees
Frame 27: Knee Adduction Angle: 87.96120536073285 degrees
Frame 28: Knee Adduction Angle: 171.60707481260752 degrees
Frame 29: Knee Adduction Angle: 104.53445508054013 degrees
Frame 30: Knee Adduction Angle: 0.0 degrees
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Fig. 4. Output 1

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Frame 1: Knee Adduction Angle: 108.43494882292202 degrees, Knee Flexion Moment: 260.5843283085151 Nm
Frame 2: Knee Adduction Angle: 150.64224645720873 degrees, Knee Flexion Moment: 134.66495730227132 Nm
Frame 3: Knee Adduction Angle: 22.166345822082455 degrees, Knee Flexion Moment: 103.63590900727752 Nm
Frame 4: Knee Adduction Angle: 173.65980825409005 degrees, Knee Flexion Moment: 30.333331582239065 Nm
Frame 5: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 6: Knee Adduction Angle: 49.02199017702011 degrees, Knee Flexion Moment: 207.37277558010047 Nm
Frame 7: Knee Adduction Angle: 146.30993247402023 degrees, Knee Flexion Moment: 152.36504989914596 Nm
Frame 8: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 9: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 10: Knee Adduction Angle: 158.96248897457818 degrees, Knee Flexion Moment: 98.60437350456016 Nm
Frame 11: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 12: Knee Adduction Angle: 1.8603909437914135 degrees, Knee Flexion Moment: 8.917278032916716 Nm
Frame 13: Knee Adduction Angle: 18.434948822922017 degrees, Knee Flexion Moment: 86.86144276950508 Nm
Frame 14: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 15: Knee Adduction Angle: 0.0 degrees, Knee Flexion Moment: 0.0 Nm
Frame 16: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 17: Knee Adduction Angle: 26.565051177077994 degrees, Knee Flexion Moment: 122.84063041192847 Nm
Frame 18: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 19: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 20: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 21: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 22: Knee Adduction Angle: 126.86989764584402 degrees, Knee Flexion Moment: 219.74400000000006 Nm
Frame 23: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 24: Knee Adduction Angle: nan degrees, Knee Flexion Moment: nan Nm
Frame 25: Knee Adduction Angle: 73.55962047831983 degrees, Knee Flexion Moment: 263.44964079254436 Nm
Frame 26: Knee Adduction Angle: 107.8297342256772 degrees, Knee Flexion Moment: 261.48729013723823 Nm
Frame 27: Knee Adduction Angle: 87.96120536073285 degrees, Knee Flexion Moment: 274.50611868396913 Nm
Frame 28: Knee Adduction Angle: 171.60707481260752 degrees, Knee Flexion Moment: 40.09253268196314 Nm
Frame 29: Knee Adduction Angle: 104.53445508054013 degrees, Knee Flexion Moment: 265.8893879881822 Nm
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Fig. 5. Output 2

VI. Conclusion

The findings of this project showcases the effectiveness of the TransPose model in properly identifying leg keypoints from video frames and computing biomechanical data, such as knee flexion angles and knee flexion moment with 6 sensors utilised for the experiment. The model exhibits potential for utilization in the fields of sports science and rehabilitation by offering a comprehensive analysis of knee mechanics. To validate the results obtained, further experiments should be performed to obtain the Knee Flexion Moment ground truth values. Nevertheless, the existence of 'nan' values in particular frames suggests the possibility of enhancing keypoint identification and angle computation. In order to improve the dependability and effectiveness of the model for practical applications, it is important for future research to focus on increasing these aspects, hence ensuring consistent and accurate outcomes in all situations.

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