Improving Knee Osteoarthritis Classification with Markerless Pose Estimation and STGCN Model

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Abstract*—Knee osteoarthritis (KOA) is a debilitating disease that greatly impacts the quality of life, particularly among the elderly population. Conventional subjective assessment methods for KOA have limitations in terms of accuracy and objective diagnosis. This paper proposes an innovative approach by integrating advanced technologies, specifically the Spatio-Temporal Graph Convolutional Network (STGCN), applied to gait analysis from markerless videos, for precise and quantitative assessment of KOA. The STGCN network is applied to normalized data obtained from Blazepose, a markerless pose estimation technique. Evaluated on an academic dataset of 80 RGB videos, it provides an accuracy of 93.75%. By leveraging the capabilities of the STGCN network, this study significantly enhances the classification of KOA based on gait patterns, offering promising prospects for improved diagnosis and treatment strategies for individuals with KOA.

***Keywords*—KOA classification, Pose estimation, Gait analysis, Deep Learning , STGCN model**

I. INTRODUCTION AND RELATED WORK

Knee osteoarthritis (KOA) is a disease that causes pain from cartilage and meniscus damage. This disease leads to walking disorders and decreases a person's quality of life. In an aging society, the number of patients who suffer from KOA is increasing. Gait analysis plays a crucial role in evaluating the condition of patients with KOA, a prevalent form of arthritis among the elderly, characterized by symptoms such as joint pain, stiffness, and reduced range of motion. Traditionally, gait analysis has relied on subjective assessments by physicians or therapists, who observe and document a patient's walking pattern, according to a rating scale like Kellgren-Lawrence (KL) and Hoehn and Yahr (H&Y). However, these scales have limited effectiveness, which hampers reliable quantitative diagnosis. To overcome these limitations, there is a growing need to integrate advanced technologies and objective methods into gait analysis, allowing for more accurate assessment and monitoring of KOA patients. Many researchers have investigated the application of machine learning technology to the classification of knee osteoarthritis. These studies have witnessed significant progress, notable advancements being made such as the introduction of pressure sensors specifically designed for shoes. These sensors have revolutionized the clinical analysis of gait by providing valuable data on pressure distribution during walking. In [1] the authors examine the effects of early-stage clinically diagnosed knee osteoarthritis on insole pressure sensors during walking at normal speeds. Their study focuses on evaluating the impact on pressure points where knee forces typically peak for individuals without knee conditions. A considerable emphasis has been placed on image-based approaches in the literature for classifying KOA. These studies utilize diverse imaging modalities, including X-ray, MRI, and depth sensors, to capture valuable information that aids in KOA classification. In [2], the authors present a methodology using Deep Convolutional Neural Networks (DCNN) to classify the severity of KOA based on X-ray images. This approach aims to reduce subjectivity among radiologists and accelerate the classification process. The experimental results highlight the superior accuracy of their proposed method compared to other KOA severity classification algorithms, achieving a significant accuracy of 77.24%. Furthermore, the use of marker-based approaches aids in the accurate detection of keypoints, enabling effective feature extraction. In [3] the authors introduce a framework that effectively classifies abnormal gait patterns associated with KOA and Parkinson's disease (PD) from normal (NM) gait. They employ a vision-based (VB) approach, leveraging a newly created and presented Vision-based Gait Dataset. Markers are employed to aid in the detection of relevant joints and specific areas associated with the disease. An enhanced segmentation technique is utilized to accurately identify the regions of interest (ROIs) where the markers are positioned. The study enables precise extraction of the necessary features, which enhances the accuracy of the classification process using KNN. In a study by [4], an RGB-D camera was employed to assess the gait of both KOA patients and healthy individuals. Kinematic and spatiotemporal (SPT) data were collected to obtain body joint information. By implementing Support Vector Machine (SVM) with this approach. In [5], the authors incorporated pain scores and gait features as key factors in characterizing KOA. They utilized spatial-temporal, kinematic, and electromyographic correlated features as relevant characteristics. Severity classes were subsequently formed and tested using an SVM classifier. The highest-performing classification model achieved an accuracy of 85.2%. In addition to the aforementioned methodologies, there exist advanced markerless techniques, including BlazePose [6], Openpose [7] and other similar approaches, which offer the capability to detect joints without the need for physical markers. These techniques leverage computer vision algorithms to accurately identify and track joint positions in real-time. BlazePose has found valuable applications in the field of human body movement analysis. For instance, in a study focused on low back pain physical rehabilitation [8] both BlazePose and OpenPose algorithms were utilized to track and analyze body movements during rehabilitation exercises. By leveraging BlazePose and OpenPose, the authors were able to estimate human pose and apply a Gaussian Mixture Model for comprehensive analysis. This research demonstrates the potential of BlazePose in accurately assessing and improving movement patterns, particularly in clinical settings such as physical rehabilitation. These markerless techniques, based on deep learning models most of the time, offer significant advantages in joint detection. Additionally, leveraging DL models such as Spatio-Temporal Graph Convolutional Network (STGCN) [9] for classification purposes is a promising direction. Given the predominant use of machine learning architectures in related studies, the utilization of STGCN, a powerful DL model, is a logical and advantageous choice. The abundance of research on STGCN in this domain provides valuable insights and demonstrates its efficacy. Therefore, in this paper, we propose to employ STGCN for knee osteoarthritis (KOA) classification using normalized data extracted from Blazepose, a markerless pose estimation method. By leveraging Blazepose, which enables efficient joint detection, we aim to accurately classify KOA based on gait patterns. Through this integrated approach, we expect to improve accuracy and reliability in the classification of KOA.

The remainder of this article is organized as follows: Section 2 presents an extensive overview of the materials and methods employed in this study. This includes a description of the utilized database and the Blazepose-STGCN Pipeline, which entails the application of BlazePose for keypoint tracking, as well as the implementation of STGCN for classification purposes. In Section 3, we conduct experiments specifically aimed at classifying Knee Osteoarthritis (KOA). The last section concludes the paper and gives some future perspectives.

II. MATERIAL AND METHOD

A. Gait Dataset

In this paper, we used a publicly accessible dataset called "Gait Dataset for Knee Osteoarthritis and Parkinson's Disease Analysis With Severity Levels'' [10] for our research. The dataset comprises 96 subjects which involves 50 KOA, 16 Parkinson's Disease (PD) and 30 Normal/Healthy (NM) subjects. Notably, this dataset encompasses not only lower body (limbs) movement but also upper body (arm, posture) movement. The KOA and PD data were collected from different hospitals, and healthy volunteers were also enrolled to analyze the gait deviations. Expert clinicians evaluated the severity of the diseases using the KL and H&Y scales for KOA and PD respectively, as referenced in the works of [11] and [12]. The dataset consisted of video recordings captured by a single NIKON DSLR d5300 camera positioned 8 meters away from the walking mat within the hospital area. To facilitate tracking, a set of 6 red-colored passive reflective markers were attached to the joints of each subject.

The primary objective of this dataset is to examine the deviations observed in the gait of patients compared to that of individuals with normal gait. Our particular focus in this paper is on patients diagnosed with KOA. A brief description of the dataset is provided in Table I.

TABLE I. BRIEF DESCRIPTION OF THE KOA-PD-NM DATASET SHOWING SUBJECTS INVOLVED AND THE RELATED DEMOGRAPHIC DATA

Gait type	**Severity level**	**Avg. age (in years)**	**Avg. height (in m)**	**# Subjects by Gender**
Normals	Healthy/ Normal (NM)	45	1.6	30: 17F, 13M
Knee osteo-arthritis (KOA)	Early (EL)	47.1	1.54	15: 14F, 1M
	Moderate (MD)	59.8	1.58	20: 12F, 8M
	Severe (SV)	62.4	1.54	15: 12F, 3M

B. Blazepose-STGCN Pipeline: 3D Keypoint Tracking for Knee Osteoarthritis Classification

The proposed pipeline for knee osteoarthritis classification from videos is detailed in this section, with its multiple interconnected steps. Initially, the videos are processed using the BlazePose technique, which extracts and tracks body joints to obtain a sequence of 3D skeletal keypoints with (x,y,z) coordinates. Data normalization is then applied to ensure consistency and remove any biases or variations. This normalization step aids in standardizing the input data across different samples, accounting for differences in camera positions and subject sizes. The data is now a sequence of graphs, whose nodes are body joints, labeled with their 3D coordinates and other features if needed. These features are then fed into the STGCN that generates classification results to differentiate between normal and abnormal subjects, specifically detecting cases of KOA from a binary softmax classifier.

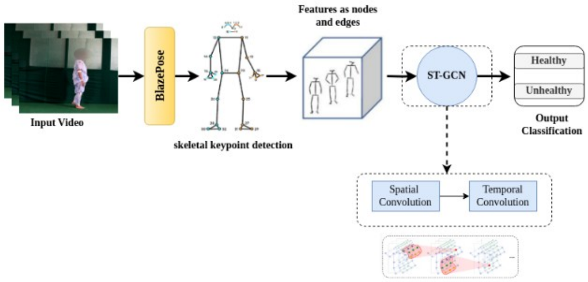

Fig. 1. BlazePose-STGCN Pipeline

1) *Skeleton extraction using BlazePose: Markerless Joint Detection*

In this study, we utilized the advanced technique of BlazePose for video analysis. BlazePose is a markerless joint detection method that predicts $(x, y, z$¿ coordinates for each joint from weakly controlled videos, unlike traditional methods that require placing markers on subjects [3],[10]. One of the remarkable features of BlazePose is its ability to detect and track 33 joints of the human body. These points represent crucial anatomical landmarks such as the shoulders, elbows, wrists, hips, knees, ankles, and so on (Fig. 2). By capturing these key points, BlazePose provides a compact and comprehensive representation of the body's pose and movement. The core idea behind BlazePose is to employ a deep neural network architecture to infer the 2D and 3D locations of joints from RGB images or video frames. The network was trained on vast amounts of labeled data, enabling it to learn the spatial relationships and appearance patterns of different joints. This allows for robust and precise joint detection even in complex and dynamic scenarios [6]. Furthermore, one of the notable features of BlazePose is its real-time performance: it runs at high frame rates, allowing for instant tracking and analysis of all 33 joints. This augmentation in the number of articulations significantly improves upon the previous work, which only utilized six joints [3].

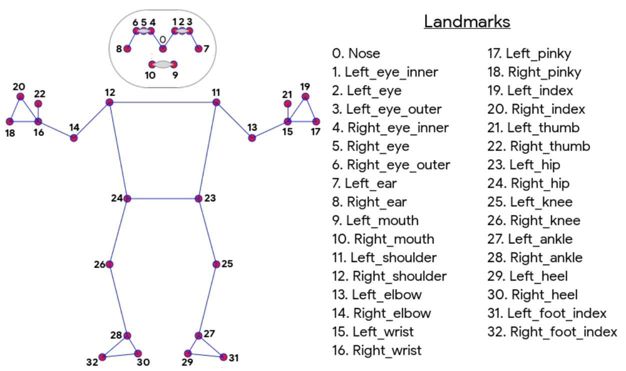

Fig. 2. BlazePose: Joint Detection Visualization [6]

Formally, we focus on tracking K body joints during a walking sequence captured on a video with T frames, for which BlazePose yields a sequence of 3D coordinates:

$$\{(x_i^t, y_i^t, z_i^t); i=1 \ldots K, t=1 \ldots T\}.$$

The resulting skeleton sequence, as shown in Fig.3, summarizes the gait of the subject.

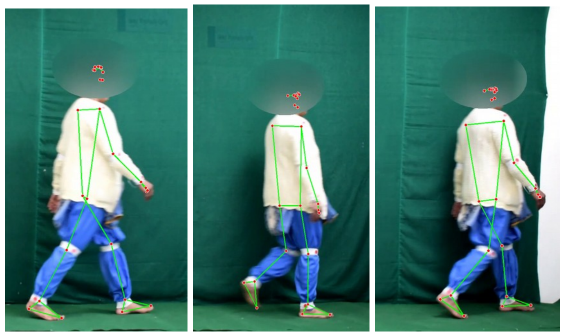

Fig. 3. Illustrative skeletal gait sequence using BlazePose

2) *Data normalization*

In the study, to ensure consistent and comparable analysis of the (x, y, z) coordinates across different subjects, we applied the min-max normalization to the data. It rescales the coordinates to a standardized range, thus focusing on the relative positions and movements of the joints rather than absolute values. This approach accounts for variations in physical characteristics, ensuring that the relative movements and patterns are accurately captured during subsequent analysis.

3) *STGCN-KOA: Spatial-Temporal Graph Convolutional Network for Knee Osteoarthritis Classification*

The STGCN [9] is a pioneering action recognition model that utilizes Graph Convolutional Networks (GCN) on skeleton data. We are currently adapting this system for the classification of KOA pathology. STGCN is a DL architecture specifically designed to handle spatio-temporal graphs, making it highly suitable for tasks that involve sequential or time-dependent information. The network operates on data represented as a graph, where the nodes are labeled by features. Fig. 4(a) provides a visual representation of this structure, where each node represents a joint. Intra-skeleton edges are defined based on mechanical connections between joints, while the inter-image edges connect the same joints across consecutive images to indicate their trajectory [9].

- *Graph structure construction*

Our primary emphasis is directed towards the construction of the Spatio-Temporal Graph structure. So to construct it from a sequence comprising K nodes and T frames [9], we employ a pose graph G = (V,E). The node set $V=\{v_t^i \vee i=1 \ldots K, t=1 \ldots T\}$ denotes the joint positions, where v_t^i represents the *i*-th joint at the *t*-th frame [9]. The 4-dimension feature vector of v_t^i consists of 3D coordinates of joints and the confidence score. The edge set E includes: the intra-skeleton connections, which connect the nodes of each frame according to the human body, where these edges form a spatial edge that we denote as $\{v_t^i v_t^j \vee (i, j) \in h\}$, where h is a set of human members or body parts. Then the inter-frame connections that connect the same joints in consecutive frames form the temporal edges that we denote as $\{v_t^i v_{t+1}^i\}$.

- *Sampling and partitioning Strategies*

Now to understand how the STGCN works, it is essential to first introduce its sampling and partitioning strategies. Dealing with convolutions on 2D images is straightforward using a regular grid with a rectangle representing the spatial support. However, in the context of graphs, the topology is no longer regular and the spatial support (neighborhood) of each processed point is defined as its adjacent nodes. Fig. 4(b) illustrates this concept for a single frame: the surrounded nodes represent the sampling area of the convolutional filter applied to each red point. In summary, the ***sampling strategy*** employed by STGCN [9] is based on mechanical dependencies between joints rather than spatial vicinity.

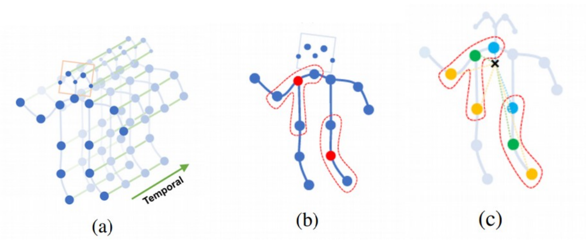

Fig. 4. **(a)** Sequence of skeleton graphs, denoting human movement in space and time. **(b)** Sampling strategy of a convolution layer for a single frame. **(c)** Spatial Configuration Partitioning strategy [9].

Now the ***partitioning strategy*** aims at grouping joints according to characteristics of human movements, that may be categorized [9] into concentric or eccentric movements, and the points in the sampling region are divided into three subsets:

- The root node (or center joint), highlighted in green in Fig. 4(c).
- The centripetal group (highlighted in blue in Fig. 4(c)), consisting of the closest nodes to the center of gravity of the skeleton (depicted as the black cross).
- The centrifugal group (highlighted in yellow in Fig.4(c)), which includes the most remote nodes from the center of gravity.

In STGCN, the center of gravity is determined as the average coordinate of all skeleton joints in a frame. Using Spatial Configuration Partitioning [9], each joint is assigned a label based on partitions. These partitions establish distinct weights for the model, facilitating accurate spatial analysis and learning. To capture the temporal dimension, STGCN extends the concept of graph convolution discussed earlier by considering this dimension as a sequence of consecutively stacked skeleton graphs, as shown in Fig. 4 (a). This leads to a collection of neighboring graphs. Since each joint in a graph must be connected through an edge to its corresponding joint in the previous and next neighboring frames, STGCN effectively applies spatiotemporal convolutions to the human pose sequence data.

- *Model architecture*

Fig. 5 illustrates the architecture of the STGCN model employed in this study. The network consists of ten blocks of spatiotemporal graph convolution operators, also known as STGCN units. The first four blocks have 64 output channels, blocks 5–7 have 128 output channels, and the remaining blocks have 256 output channels. All of these blocks adopt a temporal kernel size of 10, i.e. the filter takes into account the current time step and the nine adjacent time steps in the sequence. By convolving the filter over the temporal dimension, the model captures patterns and relationships within this ten-step window, allowing it to analyze the temporal dynamics and dependencies present in the data. To prevent overfitting, the weights update is randomly dropped with a probability of 0.5. The stride is set to 1 for all layers except the fourth and seventh layers, where it is set to 2 to behave like a pooling layer. The resulting tensor is then passed through a global pooling function, yielding a feature vector with 256 dimensions for each sequence.

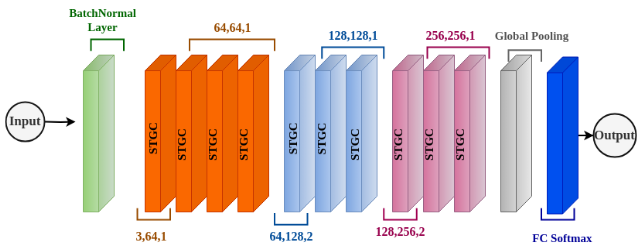

Fig. 5. The architecture of STGCN

Each STGCN (Fig.6) unit begins by extracting relevant features from the intra-skeleton set using a GCN layer. The output of this GCN sub-module has the same size as the input and serves as a learned representation of the skeleton. These learned features are then passed as input to a Temporal-GCN (TCN) sub-module, which captures inter-frame information using a fixed temporal window size. Finally, the combined spatial and temporal feature vectors are fed into a SoftMax classifier.

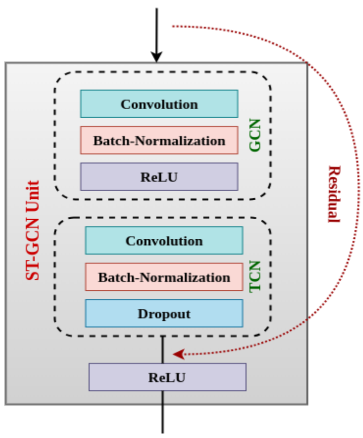

Fig. 6. ST-GCN Unit

III. EXPERIMENTATION

A. Implementation details

1) Frames Extraction and pose estimation

The videos analyzed in this study had a maximum of 1000 frames per video, which served as the baseline for the data collection. The parameters for minimum detection confidence and minimum tracking confidence were both set to the default value of 0.5. The dataset comprised a total of 80 videos (30 videos featuring individuals without any health issues (NM) and 50 videos with subjects affected by KOA), which were divided into training (80%), and testing (20%) sets.

Only one person was present in each video. The parameters are shown in Table II, and so the input data have a dimension of C × T × V = 99 000

TABLE II. TRANSFORMED DATA : PARAMETERS OVERVIEW

Parameter	Representation	Value
Number of channels	C	3
Number of frame per video	T	1000
Number of joints	V	33

2) Working environment

In this study, the STGCN model was implemented using PyTorch in an Ubuntu environment. The hardware setup included an NVIDIA GeForce GTX 1050 GPU with 16 GB memory and an Intel Core i5 9300H processor. We leveraged CUDA, OpenCV, and other essential libraries to facilitate the training and testing of KOA gait classification model.

3) Hyperparameters and training details

The STGCN network was trained for 120 epochs with a batch size of 8. A learning rate of 0.01 was chosen and at epochs 40 and 80, the learning rate was reduced by a factor of 10. The SGD optimizer was used with a weight decay of 10^{-4}. To prevent overfitting, a dropout rate of 0.5 was used. (Table III).

TABLE III. HYPERPARAMETER AND THEIR VALUES

Hyperparameters	Value
Optimizer	SGD
Epochs	120
Learning rate	0.01
Dropout rate	0.5
Batch size	8

B. Evaluation

1) Performance metrics

In our context, True Positive (TP) indicates the number of patients correctly classified as KOA, while True Negative (TN) counts the individuals correctly classified as healthy. False Positive (FP) counts healthy individuals misclassified as KOA, and False Negative (FN) counts KOA patients wrongly classified as healthy.

Accuracy (ACC) provides an overall indication of how well the classification model performs in distinguishing between KOA and healthy cases:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

A high sensitivity (or recall) means there are few disease omissions:

$$Sensitivity=\frac{TP}{TP+FN} \quad (2)$$

A high specificity means that the model can rule out most subjects with no disease:

$$Specificity=\frac{TN}{TN+FP} \quad (3)$$

Precision measures the proportion of people with KOA among those classified as such:

$$Precision=\frac{TP}{TP+FP} \quad (4)$$

The F1-Score combines the results of precision and recall:

$$F1-Score=\frac{2*(precision*Recall)}{Precision+Recall} \quad (5)$$

2) Discussion and results

In this section, we present and discuss the performance achieved in the previous metrics to evaluate the STGCN model. Table IV provides a comprehensive overview of the metrics, while Fig. 7 presents the confusion matrix, which offers valuable insights into the model's performance by presenting a detailed breakdown of predicted and actual class labels.

TABLE IV. KOA CLASSIFICATION METRICS FOR STCGN

	Accuracy	Sensitivity	Specificity	Precision	F1-Score
NM	0.9495	0.9206	0.9389	0.9129	0.9167
KOA	0.9255	0.9366	0.9499	0.9443	0.9404
All	**0.9375**	**0.9286**	**0.9444**	**0.9286**	**0.9286**

Based on the obtained results, the proposed method using the STGCN for KOA classification has demonstrated promising performance with an average accuracy of 0.9375. Overall, the results indicate that the STGCN model successfully distinguished between healthy and unhealthy knee conditions. It exhibited high accuracy, sensitivity, specificity, precision, and F-scores for both the NM and KOA classes. These findings suggest the suitability of the STGCN model for the classification of knee osteoarthritis and normal conditions.

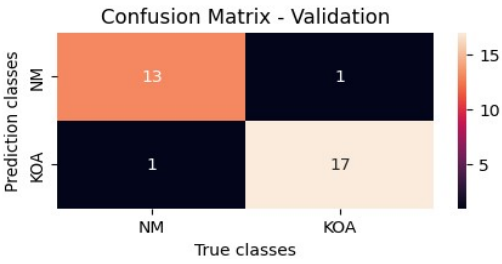

Fig. 7. Confusion Matrix

To improve the evaluation of our model, we conducted a comparative analysis by comparing the results obtained from the combination of Blazepose and the STGCN model with other state-of-the-art approaches. Specifically, we compared our results with those achieved by employing the markers approach based on K-nearest neighbors (KNN) using the same dataset [3]. In addition, we explored the use of markerless techniques, particularly Blazepose, as an alternative solution to address the challenges associated with marker-based techniques. Our goal in utilizing Blazepose was to overcome the limitations and complexities observed in [3] due to marker usage. Furthermore, we sought to demonstrate the performance of Blazepose in comparison to other techniques such as OpenPose [13]. Table V presents the average performance metrics obtained.

TABLE V. PERFORMANCE COMPARISON WITH STATE OF THE ART

Method	**Dataset**	**Train-ing**	**Avg Accuracy**	**Avg Sensitivity**	**Avg Specificity**
KNN [3]	KOA-PD-NM	Scratch	0.9179	0.8981	0.8985
WM-STGCN [13]	Youtube videos	Scratch	0.7810	0.8667	0.8750
STGCN (Ours)	KOA-PD-NM	Scratch	**0.9375**	**0.9286**	**0.9444**

Notably, our model, which leverages the Blazepose framework, exhibited superior performance in classification tasks. Achieving an accuracy of 0.9375, our model surpassed that of KNN, which achieved an accuracy of 0.9179. Moreover, across various metrics, our model consistently demonstrated superior performance when compared to KNN. The use of STGCN proved to be highly effective in our study, due to its ability to capture and analyze both spatial and temporal information. This unique feature allows for comprehensive detection and understanding of dynamic patterns. By leveraging this capability, our model was able to achieve promising performance in the classification.

IV. CONCLUSION AND PERSPECTIVES

This paper presented a novel approach for knee osteoarthritis (KOA) classification using videos. The proposed method utilized BlazePose for joint extraction and the STGCN network for classification. The results demonstrated that this approach outperformed previous machine learning techniques, achieving an significant accuracy of 0.9375. The use of BlazePose allowed for the extraction of joints without the need for physical markers, making the process more practical, and less intrusive. By leveraging the STGCN network, the proposed method effectively captured the intricate movement patterns associated with KOA, resulting in improved classification accuracy. Now there are several avenues to consider in order to enhance the proposed method. First, expanding the dataset and incorporating a large sample size would provide a more comprehensive evaluation and validation of the classification model. Moreover, it would be valuable to include markerless videos obtained under less controlled conditions, such as complex backgrounds and diverse lighting conditions. This would enable the assessment of the model's robustness in real-world scenarios. Additionally, conducting hyperparameter optimization for the model is worth considering. Fine-tuning the model's hyperparameters can potentially improve its performance. This optimization process can help identify the best configuration for the model and further enhance its classification capabilities.

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REFERENCES

[1] M. Munoz-Organero, C. Littlewood, J. Parker, L. Powell, C. Grindell, et S. Mawson, « Identification of Walking Strategies of People With Osteoarthritis of the Knee Using Insole Pressure Sensors », *IEEE Sens. J.*, vol. 17, n° 12, p. 3909-3920, juin 2017, doi: 10.1109/JSEN.2017.2696303.

[2] R. Tri Wahyuningrum, A. Yasid, et G. Jacob Verkerke, « Deep Neural Networks for Automatic Classification of Knee Osteoarthritis Severity Based on X-ray Images », in *Proceedings of the 2020 8th International Conference on Information Technology: IoT and Smart City*, Xi'an China: ACM, déc. 2020, p. 110-114. doi: 10.1145/3446999.3447020.

[3] N. Kour, S. Gupta, et S. Arora, « A vision-based clinical analysis for classification of knee osteoarthritis, Parkinson's disease and normal gait with severity based on k-nearest neighbour », *Expert Syst.*, vol. 39, n° 6, juill. 2022, doi: 10.1111/exsy.12955.

[4] X. Cui, Z. Zhao, C. Ma, F. Chen, et H. Liao, « A Gait Character Analyzing System for Osteoarthritis Pre-diagnosis Using RGB-D Camera and Supervised Classifier », in *World Congress on Medical Physics and Biomedical Engineering 2018*, L. Lhotska, L. Sukupova, I. Lacković, et G. S. Ibbott, Éd., in IFMBE Proceedings, vol. 68/1. Singapore: Springer Nature Singapore, 2019, p. 297-301. doi: 10.1007/978-981-10-9035-6_53.

[5] H. N. A. Halim et A. Azaman, « Clustering-Based Support Vector Machine (SVM) for Symptomatic Knee Osteoarthritis Severity Classification », in *Proceedings of the 2022 9th International Conference on Biomedical and Bioinformatics Engineering*, in ICBBE '22. New York, NY, USA: Association for Computing Machinery, mars 2023, p. 140-146. doi: 10.1145/3574198.3574220.

[6] V. Bazarevsky, I. Grishchenko, K. Raveendran, T. Zhu, F. Zhang, et M. Grundmann, « BlazePose: On-device Real-time Body Pose tracking ». arXiv, 17 juin 2020. doi: 10.48550/arXiv.2006.10204.

[7] Z. Cao, G. Hidalgo, T. Simon, S.-E. Wei, et Y. Sheikh, « OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields ». arXiv, 30 mai 2019. Consulté le: 13 juin 2023. [En ligne]. Disponible sur: http://arxiv.org/abs/1812.08008

[8] A. Marusic, S. M. Nguyen, et A. Tapus, « Evaluating Kinect, OpenPose and BlazePose for Human Body Movement Analysis on a Low Back Pain Physical Rehabilitation Dataset », in *Companion of the 2023 ACM/IEEE International Conference on Human-Robot Interaction*, in HRI '23. New York, NY, USA:

Association for Computing Machinery, mars 2023, p. 587-591. doi: 10.1145/3568294.3580153.

[9] S. Yan, Y. Xiong, et D. Lin, « Spatial Temporal Graph Convolutional Networks for Skeleton-Based Action Recognition ». arXiv, 25 janvier 2018. Consulté le: 14 juin 2023. [En ligne]. Disponible sur: http://arxiv.org/abs/1801.07455

[10] N. Kour, S. Gupta, et S. Arora, « Gait Dataset for Knee Osteoarthritis and Parkinson's Disease Analysis With Severity Levels », vol. 1, déc. 2020, doi: 10.17632/44pfnysy89.1.

[11] S. Bhat, U. R. Acharya, Y. Hagiwara, N. Dadmehr, et H. Adeli, « Parkinson's disease: Cause factors, measurable indicators, and early diagnosis », *Comput. Biol. Med.*, vol. 102, p. 234-241, nov. 2018, doi: 10.1016/j.compbiomed.2018.09.008.

[12] S. S. Gornale, P. U. Patravali, et R. R. Manza, « A Survey on Exploration and Classification of Osteoarthritis Using Image Processing Techniques », vol. 7, nº 6, 2016.

[13] J. Zhang, J. Lim, M.-H. Kim, S. Hur, et T.-M. Chung, « WM–STGCN: A Novel Spatio Temporal Modeling Method forParkinsonian Gait Recognition », *Sensors*, vol. 23, nº 10, p. 4980, mai 2023, doi: 10.3390/s23104980.