AI-Based Performance Evaluation System for Gatka Practitioners Using Human Pose Estimation and Skeleton-Based Action Recognition

[1] Ms. Babaljeet Kaur, [2] Anija Mittal

[1] Student, Department of Computer Applications, Guru Kashi University, Bathinda, India

[2] Assistant Professor, Department of Computer Applications, Guru Kashi University, Bathinda, India

Email Id: [1] babaljeetk00@gmail.com, [2] anijamittal@gmail.com

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Abstract— *A new addition to the sports performance analysis toolkit is Artificial Intelligence (AI), which can provide accurate and automated analysis of athletes' movements, kind of. Human pose estimation and skeleton-based action recognition enable the analysis of body movements without the need for wearable devices, as their movement can be captured from videos and studied. Notwithstanding, although these techniques are utilized on a great deal in sports, such as soccer, fitness and wellness, and karate, they are not yet in use in traditional martial arts like Gatka. In this review paper, the recent research on human pose estimation and deep learning and action recognition approaches that can really be used to assess the performance of Gatka practitioners will be explored. Based on the reviewed studies, the ability of AI models like Convolutional Neural Networks (CNNs), transformer-based approaches, and newer pose estimation frameworks to identify human actions and assess the proficiency of the technique is evident. The overall results indicate that it may be possible to use the system for objective feedback, effective training, and improving the reliability of performance scoring, when combined with skeleton-based analysis methods for pose estimation. The review also indicates that the entire process of identifying Gatka techniques, verifying posture and motion and assisting to preserve and promote this traditional martial art with modern technology is possible with the use of AI based set-up, though it may take time.*

Keywords – Artificial Intelligence (AI), Gatka, Human Pose Estimation, Skeleton-Based Action Recognition, Deep Learning, Performance Evaluation, Computer Vision.

I. INTRODUCTION

Artificial Intelligence (AI) has now become somewhat of a crucial technology in the realm of modern sports as it helps coaches and athletes analyze performance in an efficient manner. When AI is teamed up with computer vision, it can automatically spot and make sense of human body movements from pictures and videos. Skeleton-based action recognition uses the locations of the key joints to determine the action, drills and technique based on the skeleton.Pose estimation locates key joints, and skeleton-based action recognition then identifies various movements, drills and techniques based on the pose. All this and athletes receive immediate feedback, which is generally objective, reliable, and may even make a training session more effective, and reduce the need for constant supervision by hand. Gatka is a traditional Sikh martial art that uses a combination of weapon skills, coordination, footwork, balance and defense. Practitioners need to practice it regularly, with the assistance of experienced trainers, in order to master it – as well as assess it. However, the manual solution can be rather time-consuming and the results might slightly vary from one instructor to another depending on his/her background, experience, and personal judgment. An AI based performance evaluation system can help here, providing consistent, accurate and more data-informed evaluations of how a person is performing movements, and how they are executing technique.

In recent years, deep learning and pose estimation methods have achieved remarkable success in action recognition for human behaviors in diverse sports and fitness contexts, such as MediaPipe, OpenPose, and YOLO-Pose. Likewise, skeleton action recognition approaches have been reported with good recognition accuracy on body actions, most of which have employed joint coordinates together with motion patterns. It seems that a new technique in Gatka is also conceivable through AI motion analysis, not just in theory, but also in practice for the recognition of skill and overall assessment.

II. BACKGROUND & RESEARCH MOTIVATION

A. *Gatka Martial Art*

The use of Artificial Intelligence (AI) and computer vision has emerged as a valuable tool for the analysis of human motion in sports and physical activities. Unlike manual observation, AI-based systems are able to automatically identify body posture, understand actions, and assess an athlete's performance in images and video. Human pose estimation aims to extract key body parts, and skeleton-based action recognition determines the movement patterns through time, based on the position of key body parts. They have been adapted and successfully used in various sports such as fitness training, football, karate or gymnastics, for the purpose of enhancing the analysis and feedback of sports performance. Gatka is a traditional martial art of the Sikhs, a combination of fitness, discipline and culture. It consists of a number of attacking and defending skills, which demand precise body posture, footwork, balance and weapon handling. Currently, the assessment of Gatka practitioners is done primarily by experienced trainers by visual observations. This is a useful technique, but can be variable due to the trainer's experience and judgment. Furthermore, manual evaluation becomes complicated if a lot of practitioners are trained to assess or if a detailed analysis of complex movements is sought.

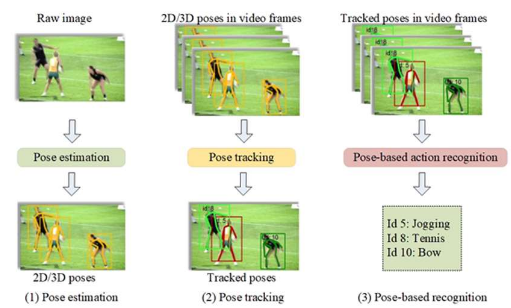

Fig 2. Shows pose estimation, tracking and recognition (Zhou, 2023)

With recent developments in pose estimation frameworks like MediaPipe, OpenPose, and YOLO-Pose, it is now possible to precisely estimate human body keypoints from a video sequence. These key points can be turned into skeleton-based features which represent the body posture and movement. These attributes, coupled with machine learning and deep learning algorithms, allow for automatic identification of Gatka techniques, assessment of movement quality and the provision of objective feedback on performance. This smart system can not only enhance training efficiency, but also help realize the digital preservation of this traditional martial art.

B. *Research Motivation*

In spite of the good result obtained with the use of AI in human action recognition in various sports, few studies have focused on automatic analysis of Gatka movements. Currently, most of the studies focus on sports activities like karate, fitness and exercise, football and general human activity recognition, whereas traditional martial arts like Gatka have been comparatively studied. Due to this, there are no benchmark datasets, special recognition models or intelligent systems developed specifically for the performance evaluation of Gatka. The other difficulty is that traditional training is often based on observation alone, and sometimes this type of feedback isn't detailed or consistent. It may be difficult to spot small posture mistakes, incorrect body alignment, or improper handling of the weapon during real time practice. An AI-powered system that can identify techniques and assess the quality of the movement can offer objective feedback, which can help practitioners enhance their skills more effectively. One of the reasons for this work is to investigate the fusion of HPE and skeleton based action recognition for getting an intelligent performance evaluation system for Gatka practitioners. A system can automatically identify various Gatka techniques and evaluate the accuracy of the posture and provide useful suggestions to trainers and learners. The plan also aims to enhance the quality of training and help sustain and promote Gatka by incorporating modern AI technologies into traditional martial arts.

III. RELATED WORK

Uçar (2025) performed a review of pose estimation and tracking in sports. The study had provided comprehensive details on the breakthroughs made by natural—human pose estimation in sports performance analysis and injury prevention, deep learning techniques (CNNs, RNNs, and Transformers. They also highlighted the importance of datasets specific to the sport, lightweight real-time models and multimodal approaches for better accuracy in dynamic sports environments. The outcomes support the implementation of AI-based assessment techniques for Gatka, with human pose estimation and skeleton-based action recognition serving as the key technologies for accurate assessment of techniques in real-time, and also supports the implementation of the AI-based human-robot interaction (HRI) system to evaluate the performance of a robot for executing a technique.

Fu (2023) proposed a fitness exercise-based HPE system with its improved YOLOv7-Pose model. The model is combined with pose estimation and action classification, which is based on the enhanced ConvNeXt backbone, optimized SPPFCSPC module and EIOU loss function, named Coordinate Attention. The authors collected a dataset of about 30000 fitness images taken from various camera angles using self-created data. The experimental results showed that the model proposed in this paper outperformed the original YOLOv7-Pose model and other state-of-the-art models (95.9 % mAP). The research reveals that the state-of-the-art pose estimation models can easily capture the movements of the body for some view angles, which means that they can be used to make use of close-to-real-time AI-based evaluation of the Gatka performance characteristics and targeting systems.

The development of a deep learning-based sports action recognition system to assess athlete's performance was developed (Li, 2024). Your framework uses 3D human pose estimation, Particle filter tracking and the Fourier descriptor-based feature extraction to achieve accurate sports movement recognition. Our system was evaluated with the battery of the MSRAction3D dataset, which are skeleton and data obtained from the Kinect. The experimental results had a recognition rate of 98.97%, showing the effectiveness of using the skeleton characteristic complement depth information to improve the overall action recognition. The proposed approach is related to the existing research since the recognition of high level and complex human actions in sports using skeleton-based approach is an effective tool for analysis and could provide useful information in developing a computer vision-based tool for evaluation of Gatka practitioners related to pose estimation and motion analysis.

Kong et al. (2022) conducted a fairly comprehensive survey on the topic of human action recognition and prediction with computer vision and deep learning technologies. It has tried a variety of model families, including CNNs, RNNs, LSTMs, Two-Stream Networks and 3D CNNs, as well as benchmark databases and evaluation strategies. Finally, the authors appeared to be in a consensus that deep learning has significantly speeded up the advancement of action recognition, but some problems emerged, including viewpoint variation, occlusion, and the lack of annotated datasets. In general, this survey can serve as a good foundation to develop an AI based performance evaluation system for Gatka practitioners by combining human pose estimation and action recognition based on skeletons.

I like this kind of comprehensive overview of the available deep learning methods for 2D/3D human pose estimation, albeit in the sense of a map of the entire area (Kappan, 2026). It reviewed cutting-edge deep learning models, then explored benchmark datasets, as well as the latest developments in single-person and multi-person image and video pose estimation. But the authors also acknowledge that deep learning has, in a rather obvious way, made pose estimation much more precise and accurate, while remaining at least somewhat intractable with issues such as occlusion, viewpoint change, complex backgrounds and real-time performance. In general, the survey will be helpful in developing a system for evaluating the performance of Gatka practitioners using AI, as in practice, the first step to skeleton-based action recognition and movement analysis is accurate human pose estimation.

In the karate posture estimation and classification, the PoseNet based mannequin was used (Aju, 2022). Firstly, you use 17 body keypoints detected by PoseNet which gives the coordinates of joints and angles between the joints are computedThen a KNN Classifier is applied to recognize different four stances in karate. Authors created their custom dataset using a WebCam and tested the proposed model with 400 samples with an accuracy of 98.75%. The results of this study proves that pose estimation and skeleton-based analysis could be good evaluations to conduct Martial arts techniques, thus, it contributes towards developing a machine learning based human performance evaluation system specifically for Gatka practitioners using human pose estimation and skeleton based action recognition.

TABLE I
SUMMARY OF REPRESENTATIVE POSE-BASED STUDIES

S.No.	Dataset	Techniques	Algorithms	Accuracy
1	Various sports datasets	Human Pose Estimation, Pose Tracking, 2D & 3D Pose Estimation	CNN, RNN, Transformer, Hybrid Networks	-
2	Self-created fitness movement dataset (~30,000 images) containing 10 exercise categories captured from different camera angles	Human Pose Estimation and Action Recognition	Improved YOLOv7-Pose with Coordinate Attention, Improved ConvNeXt, SPPFCSPC, and EIOU Loss	95.9%
3	MSRAction3D Dataset (captured using Kinect depth sensor)	3D Human Pose Estimation, Skeleton-based Action Recognition, Feature Extraction	Particle Filter Tracking, Fourier Descriptors, Skeleton & Depth Information Fusion	98.9%
4	Various benchmark action recognition datasets	Human Action Recognition, Action Prediction, Feature Extraction	CNN, RNN, LSTM, Two-Stream Networks, 3D CNN, Deep Learning Models	-

S.No.	Dataset	Techniques	Algorithms	Accuracy
5	Various benchmark 2D and 3D human pose estimation datasets	2D & 3D Human Pose Estimation, Single-person & Multi-person Pose Estimation	CNN, HRNet, OpenPose, PoseNet, Transformer-based Models, Deep Learning Frameworks	-
6	Custom Karate Pose Dataset	Human Pose Estimation, Joint Angle Calculation, Karate Pose Classification	PoseNet, Transfer Learning, K-Nearest Neighbors (KNN)	98.75%

IV. PROPOSED AI-GATKA FRAMEWORK

The aim of the proposed AI-GATKA framework is to automatically recognize Gatka techniques and to assess the skills of the practitioner by implementing AI, human pose estimation and skeleton-based action recognition. The framework consists of video of practitioners, a set of body movements obtained from the video, a set of techniques identified, and objective feedback on quality of body movements performed and postures used. This can help overcome the drawbacks of manual assessment and facilitate the accurate, consistent and timely evaluation of performance.

The framework proposed is made up of six major phases.

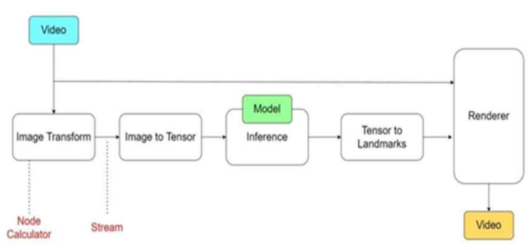

Fig. 3. Proposed AI-GATKA processing workflow

A. Data Collection

The video of the different techniques of Gatka practitioners are collected. The videos should have participants of varying skill-level and be filmed from various angles in various lighting situations. The dataset includes various basic movements in Gatka, including Ready Stance, Basic Guard, Forward Strike, Downward Strike, Left Block, Right Block, Circular Strike, and Defensive Movement. The dataset contains a variety of basic movements in the Gatka martial art, including Ready Stance, Basic Guard, Forward Strike, Downward Strike, Left Block, Right Block, Circular Strike, and Defensive Movement.

B. Video Pre-Processing

The videos collected are pre-processed to enhance the video quality prior to analysis. It involves several steps such as frame extraction, image resizing and noise removal, as well as normalization of the input data. These operations help improve the accuracy of pose detection and reduce the effect of background variations and lighting conditions.

C. Human Pose Detection

Each frame of the video is pre-processed and then processed with the MediaPipe Pose model. The model recognizes 33 body landmarks, which correspond to the main body joints such as shoulders, elbows, wrists, hips, knees, and ankles. These landmarks are a virtual image of the practitioner's posture and movement during the application of a technique.

D. Skelton Feature Extraction

This involves translating the body landmarks detected into meaningful numerical features which represent the movement of the practitioner. Some of these features are joint coordinates, joint angles, distances between body joints, direction of movement, body orientation, and speed of motion. The spatial and temporal features are combined together, which are the attributes of each Gatka technique and are used as an input for the recognition model.

E. Technique Classification

Extracted skeleton features are then used to train and test machine learning/ deep learning model for recognizing various Gatka techniques. Algorithms such as Support Vector Machine (SVM), Random Forest, Convolutional Neural Networks (CNN), CNN-LSTM, and Graph Convolutional Networks

(GCNs) can be used to classify the movements. The output of the trained model is used to compare the input features with the learned movement patterns and predict the predicted performed technique.

F. Performance Evaluation and Feedback

The recognized technique is then assessed against the reference movement that is stored in the system in the latter stages of the process (Performance Evaluation and Feedback). Measures posture accuracy, movement consistency, body alignment and technique execution. This analysis is used to create a performance score and feedback for practitioners to assist in identifying errors and enhancing their skills. Feedback is also useful for coaches to track training and more easily assess performance.

In summary, the proposed AI-GATKA approach combines computer vision and machine learning techniques to develop an automated intelligent system for assessing Gatka performance. The framework can enhance the quality of training, facilitate the development of skills, and help preserve Gatka's tradition by integrating modern AI technologies with traditional martial arts.

V. METHODOLOGY

A. Dataset and Pre-processing

The data set has 250 samples obtained from 5 different Gatka classes and 5 techniques per class (50 samples per technique). The data has been split into an 80% training population (200 cases) and a 20% testing population (50 cases). Cleaning video frames prior to landmark extraction to remove corrupted frames and standardize the video.

TABLE II

PROPOSED TECHNIQUE CLASSES

Technique	Operational Description
Basic Stance (C1)	Ready posture before an offensive or defensive action
Forward Strike (C2)	Weapon movement directed linearly toward the opponent
Defensive Block (C3)	Protective action intended to intercept or redirect an attack
Side Movement (C4)	Lateral repositioning while preserving balance and readiness
Circular Movement (C5)	Rotational movement coordinated with weapon handling

B. Feature Formulas and Representations

Each keypoint landmark i at frame t is represented as $P_i^{(t)} = (x_i, y_i, z_i, v_i)$, where v_i denotes visibility confidence.

Joint Angle Calculation (Critical for Injury Analysis)

Joint angle using vector dot product:

$$\theta = cos^{-1}\left(\frac{\vec{a}\,.\vec{b}}{\|\vec{a}\|\,\|\vec{b}\|}\right)$$

Where: $\vec{a}\,.\vec{b}$ = bone vectors

Example: Knee angle in ACL injury analysis (Yeh Y.-C. T.-S.-Y.-H., 2025)

Angular Velocity & Acceleration

$$\omega = \frac{d\theta}{dt}$$

$$\alpha = \frac{d^2\theta}{dt^2}$$

High angular acceleration often correlates with injury risk. (Yeh, 2025)

VI. EXPERIMENTAL SETUP

The proposed implementation is based on Python, OpenCV, MediaPipe Pose, NumPy and Pandas, and scikit-learn which are employed for frame processing, extracting landmarks, preparing the features, and implementing the conventional machine-learning models. Prototype development can be done on a standard desktop or laptop computer, with a minimum of an Intel Core i5 processor, 8 GB of RAM, and an HD camera. The performance of the deployment in real time is dependent on resolution, frame rate, complexity of the model and hardware acceleration.

TABLE III

SOFTWARE AND HARDWARE CONFIGURATION

Component	**Specification**
Programming language	Python
Computer vision	OpenCV
Pose estimation	MediaPipe Pose
Machine learning	Scikit-learn
Data processing	NumPy and Pandas
Processor	Intel Core i5 or higher
Memory	Minimum 8 GB RAM
Camera	HD webcam or equivalent
Operating system	Windows 10/11 or Linux

VII. RESULTS & DISCUSSION

According to the source manuscript the Support Vector Machine, Random Forest and Neural Network had prototype accuracy of 86%, 91% and 94%. The Neural Network is thus the most accurate of the three, with the reported accuracy of 78.3% compared to 75.3% for Random Forest and 70.3% for SVM. The pattern is consistent as a neural model can accommodate the non-linear relationships between a number of joint and motion features. The accuracy values reported however should be considered in conjunction with the sampling protocol, class balance, independence of the participants and the lack of class-wise metrics.

TABLE IV

REPORTED MODEL ACCURACY

Model	**Accuracy**
Support Vector Machine	86%
Random Forest	91%
Neural Network	94%

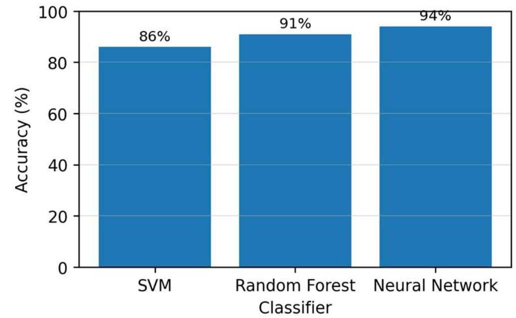

Fig. 4. Reported classification accuracy of the three models.

There are several things which can decrease the quality of the recognition. Body-only pose models may not be a direct representation of fast-moving weapons. Wrists, elbows or lower-limb landmarks could be obscured by extreme camera angles and/or self-occlusion. Landmark confidence may be decreased with lighting and background variation. Lastly, the practitioner can perform the same technique by a valid style of variation. Practitioner-independent testing, landmark-confidence filtering, temporal sequence modelling and integration of weapon detection/tracking are motivators for these issues.

VIII. APPLICATIONS

The proposed framework is able to facilitate interactive training by comparing the movement of learners with examples validated by instructors and give a general idea of the deviation in the stance, alignment and timing of the movement of the learner. It can help teachers to create uniform initial measurements and session histories. Video and landmark repository could also aid in Digital Preservation of Gatka techniques. Further validation could be expanded to mobile coaching, remote practice review, competition analysis and Augmented/Virtual reality learning environments.

IX. LIMITATIONS & FUTURE WORK

Proposed AI-GATKA framework is an effective framework for recognizing and evaluating Gatka techniques, but has a few drawbacks. First, the dataset used is relatively small, with just 250 instances, which could mean that the model has limited ability to transfer to new data and intricate variations in motion. First, the data set has a limited size (only 250 instances), which may reduce the model's capacity to generalise and be able to deal with unseen data and complex variations in motion. Second, the pose estimation model is mainly designed for detecting the landmarks of human body rather than the geometry or position of the Gatka weapon like sticks or swords. Consequently, some of the motions of a weapon are not fully captured by the system which can affect the performance evaluation. One of the drawbacks is the lack of cross-practitioner validation with different physical characteristics, different skill levels and age groups. The robustness and adaptability of the framework to a larger population may be impacted when applying it.

The proposed framework of AI-GATKA can be further enhanced in future by increasing the number of practitioners and shooting videos from various angles. This model would be more robust and perform better if it had a more varied dataset. Furthermore, it is possible to combine object detection algorithms like YOLO to explicitly track the Gatka weapons, which will enable simultaneous analysis of both body movement and weapon movement. Advanced spatio-temporal deep learning techniques, including Long Short-Term Memory (LSTM) networks and Spatial-Temporal Graph Convolutional Networks (ST-GCN), can also be employed in future research to model the temporal evolution and spatial relationships of intricate Gatka techniques. These improvements can improve the recognition accuracy, give detailed performance analysis and help to build an intelligent coaching system in real-time for Gatka practitioners.

X. CONCLUSION

This review focuses on the advantages of Artificial Intelligence, Human Pose Estimation and Skeleton based Action Recognition to aid the performance evaluation of Gatka practitioners. This research proposes a framework called AI-GATKA, which integrates the video processing, pose estimation, skeleton feature extraction, and machine learning to automate the recognition of Gatka techniques and to give objective performance feedback. The results show that AI has the potential to enhance training practices, minimize subjectivity when evaluating Gatka, and aid in the digital preservation of Gatka. Looking forward, the study will include experiments with more data, the tracking of weapons, and more complex deep learning models to improve the accuracy of the system and its applicability to real-world situations.

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