A Risk Assessment Tool to Identify Incorrect Human Postures

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***Abstract* – The purpose of this research project is to develop a posture risk assessment tool for humans using Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA) methods. The tool will be designed to evaluate the ergonomic risk factors associated with poor posture, such as musculoskeletal disorders and repetitive strain injuries. The study will involve collecting data on posture and ergonomic risk factors from a diverse group of participants and process it using Computer Vision techniques. The results of this research project will have significant implications for workplace safety and employee health, as the tool can be used to identify potential ergonomic hazards and prevent musculoskeletal disorders in workers.**

***Index terms:* Body posture, Ergonomic risk, Pose estimation**

I. INTRODUCTION

Incorrect and poor posture is a serious occupational risk that can result in musculoskeletal disorders and repetitive strain injuries. Consequently, the demand for precise tools that can evaluate posture risk and aid in preventing workplace injuries is on the rise. The purpose of this study is to create a posture risk assessment tool that utilizes computer vision technology and ergonomic assessment approaches like Rapid Entire Body Assessment (REBA) and Rapid Upper Limb Assessment (RULA). The tool uses Mediapipe, an open-source computer vision library, to detect and monitor significant body landmarks in real-time. By analysing the positions and movements of these landmarks, we can recognize possibly hazardous postures that may cause ergonomic injuries. Subsequently, RULA and REBA techniques are utilized to evaluate the ergonomic risk variables linked with each identified posture, such as muscle strain, joint stress, and exhaustion. To verify the accuracy of the tool, we performed experiments with human participants. The participants were asked to execute various tasks in front of a visual recording device such as a camera. We then compare the posture risk assessments produced by our tool to those of a manual assessment. The expected results of this research project are twofold. We aim to demonstrate the potential of computer vision technology in ergonomic assessments and contribute to the growing body of research on the use of machine learning and computer vision in occupational health and safety.

II. RELATED WORK

Several researchers have developed computer vision-based systems to evaluate worker posture and provide corresponding results with feedback to improve it. In a paper titled Light-Weight Seated Posture Guidance System authored by Rithik Kapoor, Fillia Makedon and Ashish Jaiswal, and [1] explains how to combine pose estimation and posture classification to monitor worker posture and classify it as good or bad. They used the BlazePose model to extract the critical key body points and a machine learning model to classify postures. However, their system was limited in that it could not determine posture-related risks or provide real-time feedback during workouts.

Enrique Piñero-Fuentes, Antonio Rios-Navarr, and Manuel Domínguez-Morales [2] in their proposed that used convolutional neural networks to evaluate worker posture in real-time. They used a skeleton estimator trained on the COCO dataset to estimate joints and evaluated shoulder alignment, neck lateral bend, and arm position to provide feedback. However, they evaluated only random frames from video input and aimed to develop an automatic recommendation system for detecting incorrect postures in real work scenarios.

Ze Li, Ruiqiu Zhang, Ching-Hung Lee, and Yu-Chi Lee [3] developed a system called Quick Capture that used the REBA tool to assess MSD risks associated with various postures. The system had four components, including a skeletal recognition system and a REBA-based risk calculator. However, it was limited in that it could not consider factors like force/load or coupling through images alone.

Prabesh Paudel and Kyoung-Ho Choi proposed a Worker's Pose Estimation system based on Deep Learning [4] that calculated RULA and REBA scores for 2D poses using CMU Open Pose as the baseline algorithm for detecting key points. They divided the body into two parts to calculate angles for the neck and arms. However, their system was limited in that it required a 2D pose and did not consider 3D postures.

Other methodologies include [7] the ergonomic risk assessment of lower limb movements using inertial sensors and machine learning algorithms as proposed by M. Akbari, M. Karimi, and M. Ahmadi. [8] "A Vision-Based Framework for Ergonomic Assessment of Manual Material Handling Tasks" by J. Zhang, J. G. Andrew, Y. Zhang, and Y. Wang describes the utilisation of a vision-based framework for ergonomic assessment of manual material handling tasks. The article discussed the techniques and corresponding tools for tracking body landmarks along with the integration of the REBA method for ergonomic assessment.

Quantitative approaches like REBA and RULA are commonly used to evaluate postures in industries, as they help identify the root cause of incorrect postures and optimize workspaces accordingly [6]. These tools assess body segments individually and define risk levels based on scores.

III. METHODOLOGY

Firstly, collecting a large dataset of images and/or videos of people in different postures is essential for training and testing the model. We used Mediapipe to detect body keypoints from the input images or videos. This will involve setting up the appropriate pipeline and configuring the PoseNet and/or Holistic models.

Once the keypoints are detected, the next step is to extract relevant features such as joint angles, body segment lengths, and joint velocities. These features will be used to calculate the risk score associated with the detected posture using the REBA and RULA algorithms.

Another key component is the user interface that allows users to input images or videos, view the detected poses, and see the calculated risk scores. This was created using a framework called Streamlit. To ensure the tool produces accurate results, it was important to test unit by unit. Finally, the tool was deployed to a cloud-based platform making it available for use in real-world settings.

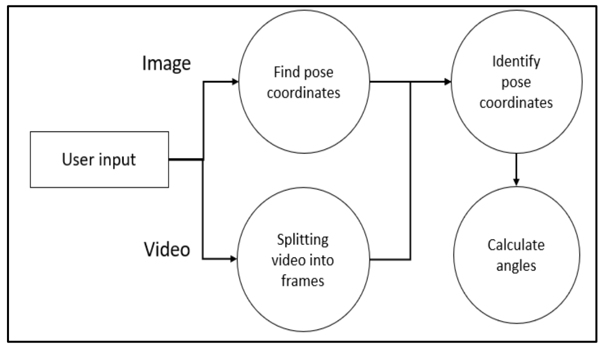

Figure:1 System Design for Processing input

A. Posture Estimation

BlazePose, a real-time pose estimation model, accurately and efficiently detects 33 2D human body keypoints, including those for the torso, arms, and legs. Convolutional neural networks (CNNs) predict keypoint locations in images or video frames, with an architecture designed to be computationally efficient for real-time inference on low-power devices. The pose detection network identifies the region of interest (ROI) where the person is located and estimate the 2D pose keypoint locations within the ROI, and a landmark regression network to refine the predicted keypoints by adjusting the coordinates. By analyzing keypoint landmarks, hazardous postures, such as forward head posture, slouching, or excessive bending, that could lead to ergonomic injuries are detected. BlazePose offers a promising approach for posture risk assessment tools, improving workplace safety, and preventing musculoskeletal disorders.

To use Mediapipe's BlazePose model for video inputs were imported the necessary libraries, including the Mediapipe library and other libraries required for reading and displaying video frames. The video is processed using a library like OpenCV, reading the frames of the video one by one. Each frame was converted to RGB format and resized it to the appropriate size to prepare it for BlazePose. Then, the pose detection modal was applied to each frame using Mediapipe's "run" method to detect the pose landmarks.

Once the pose landmarks for each frame was identified, additional post-processing steps were carried out to refine the results. For every landmark identified, the x, y and x coordinates were extracted and sent to the next module for analysis.

B. Analysing Posture

The very first step after obtaining the coordinates is to find out the profile of the person with respect to the camera. The person could be facing the camera or away from it. Posture analysis for a person facing to the left or right-side would focus only on that side of the body.

The body angles were calculated using trigonometric operations such as tangent and cosine. The coordinates provided by the pose detection model for each keypoint was used for the calculations. For example, to calculate the angle between the shoulder and elbow, we use the coordinates of the shoulder, elbow, and wrist keypoints.

To calculate the angle of a limb with respect to the ground, we first need to estimate the orientation of the limb in 3D space using pose estimation. Then, we can project it onto a 2D plane that is perpendicular to the ground, such as the image plane from a camera.

Next, we needed to calculate the angle of the limb with respect to a horizontal reference line, such as the x-axis of the image plane. One way to do this is by using the dot product and inverse cosine. We started by calculating the unit vector that represents the direction of the limb in the image plane. We subtracted the 2D coordinates of the joint at the base of the limb from the 2D coordinates of the joint at the end of the limb and then normalize the resulting vector.

After we had the unit vector, we calculated the dot product between the unit vector and a horizontal reference vector, such as (1,0). We then took the inverse cosine of the dot product to obtain the angle in radians. Finally, we converted the angle to degrees by multiplying it by 180/pi.

Another method we used to calculate the angle of a limb with respect to the ground is by using the `atan2` function. This formula takes the 2D coordinates of two joints representing the base and end of the limb and calculates the angle in radians with respect to the x-axis. We can then convert the angle to degrees by multiplying it by 180/pi.

These methods assumed a horizontal ground plane and did not take into account other factors that may affect the angle of the limb with respect to the ground, such as the height of the person or the slope of the ground. Additionally, these methods assume that the limb is projected onto a 2D plane perpendicular to the ground and that the limb is straight and not bent. If the limb is bent, a more complex formula may be needed to calculate the angle, such as the law of cosines.

By analysing the angles of the body segments, we determined whether a posture is within the acceptable range of motion or if it poses a risk of musculoskeletal injury.

It was observed that the accuracy of the body angle calculations depended on the accuracy of the keypoint detections provided by BlazePose. Additionally, some postures may require more complex calculations involving multiple keypoints and angles to fully capture the position of the body. The final step was to identify if the person is sitting or standing. This was done by calculating the angle at the knees.

C. Risk Assessment

The most important module of the proposed project is the risk assessment module that assesses the ergonomic risk associated with a detected posture. The module carries out a series of steps, including mapping, calculation, aggregation, and thresholding, to generate an overall risk score and associated risk level.

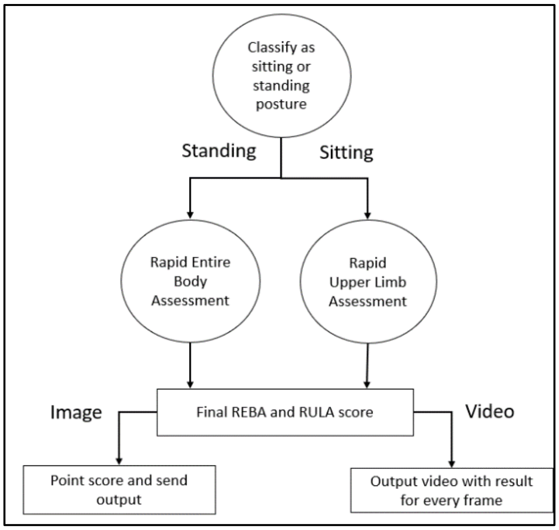

Figure:2 System design for Analysing Posture

The input to the module is the extracted features from the previous module, such as joint angles, body segment lengths, and joint velocities. These features are mapped to the relevant risk factors identified by the REBA and RULA algorithms. For instance, the neck angle would be mapped to the risk factor for neck posture.

The module then calculates the risk score for each identified risk factor based on the mapped features. This involved applying the relevant scoring criteria established by REBA and RULA.

The individual risk scores are aggregated into an overall risk score for the detected posture. The aggregation process may involve weighting the individual scores based on their relative importance and summing them to obtain the overall risk score.

Finally, the overall risk score was compared to established thresholds to determine the level of risk associated with the detected posture. The module output the overall risk score and associated risk level to the user interface, where it gets displayed alongside the detected pose. This information can be valuable for preventing ergonomic injuries and improving workplace safety.

D. Processing a Real-time Video

Video captured from a web camera requires a different approach compared to normal video uploads. We made use of Streamlit's webrtc_streamer API to set various parameters to customize the media to stream, such as resolution, frame rate, and encoding format.

WebRTC is a popular open-source project that enables real-time communication between web browsers and mobile applications without the need for a third-party plugin or software. Streamlit provides built-in support for WebRTC streaming, allowing for easy integration of real-time audio and video in applications.

The initial step involved capturing the video stream from the camera using OpenCV's cv2.VideoCapture function. This returned a video capture object that can be used to read frames from the video stream. Subsequently, the frames can be processed to detect human poses and assess the ergonomic risk associated with those poses.

To detect human poses, we use Mediapipe to estimate the location of key points on the human body, such as the joints and limbs. These key points can then be used to calculate the angles between the various body segments and assess the ergonomic risk associated with the pose. Since the person is assumed to be sitting in front of a camera while working, we only focus on the neck and trunk joints.

Initially, the alignment of the person with respect to the camera is determined by calculating the distance between the two shoulder joints. If this distance falls within the range of 0 to 4, it implies that the person is facing away from the camera, i.e., towards the sides. The person's profile is used to classify the neck and trunk angles.

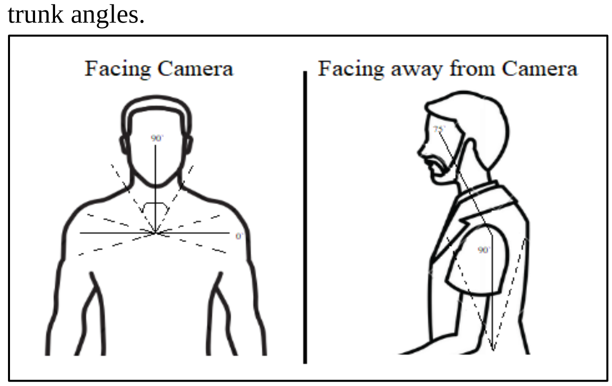

Figure:3 Neck and Trunk angles for Real time Analysis

For a person facing the camera, the neck angle is calculated by finding the angle of the line joining the mid-point between the two shoulders and the nose. The trunk angle is calculated by finding the angle of the line joining the shoulders. The optimal range for neck and trunk angles for good posture is between 88 to 90 degrees and 0 to 4 degrees, respectively.

For a person facing away from the camera, the neck angle is calculated by finding the angle of the line joining the mid-point between the two shoulders and the left or right eye. The trunk angle is calculated by finding the angle of the line joining the shoulder and the hip joints. The optimal range for neck and trunk angles for good posture is between 74 to 78 degrees and 85 to 95 degrees, respectively.

IV. TESTING

The proposed posture risk assessment system was tested through various stages to ensure its accuracy and functionality. During the initial testing phase, the Mediapipe pose detection module was tested to ensure that it accurately detected the keypoint landmarks on the human body. The mapping module was also tested to ensure that the extracted features were correctly mapped to the relevant risk factors identified by the REBA and RULA algorithms.

Next, the calculation module was tested to ensure that the risk scores were being calculated correctly based on the mapped features and the established scoring criteria. The aggregation module was then tested to ensure that the individual risk scores were weighted and summed correctly to obtain the overall risk score.

Integration testing was performed to test the various modules and components of the system together to ensure that they functioned correctly when integrated. A set of test cases was developed to cover the different combinations of inputs and interactions between the modules. The test cases verified that the modules communicated correctly and that the data was being passed between them in the expected format.

During integration testing, error handling and exception handling were also covered, such as when unexpected or invalid inputs were entered. This helped to ensure that the system was robust and able to handle a range of inputs and scenarios.

IV. RESULTS AND OBSERVATIONS

The study involved identifying the critical body joints that play a major role in classifying if a particular posture is prone to an MSD or not. The application is capable of accepting images and videos as inputs. It can also record the movements of a person live through a webcam. The application produces an image depicting all the body joints and displays the score. For video inputs, another video is generated by the application that shows the score calculated for every frame. During live monitoring, the application observes the person's movements in real-time and gives warnings to the user to correct his/her posture.

The tool showed high accuracy and reliability in assessing posture risk levels, which has potential applications in improving workplace safety and preventing musculoskeletal disorders. The study concludes that the posture risk assessment tool using RULA and REBA algorithms has the potential to be an effective means of identifying and mitigating ergonomic risks associated with poor posture.

V. CONCLUSION

In conclusion, the posture risk assessment tool developed using the RULA and REBA algorithms shows promising results in accurately identifying high-risk postures and providing risk scores for them. The tool has the potential to improve workplace safety and prevent musculoskeletal disorders. However, the study also revealed some limitations and areas for improvement, such as the need to enhance the accuracy of the Mediapipe pose detection output and incorporate other risk factors beyond those identified by RULA and REBA. Future research can explore the inclusion of various factors like durations, load, sequence of movements, etc to further enhance the performance of the tool. Additionally, increasing the accuracy and speed of the application as a whole is also essential.

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