OpenPosture Results

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To capture results for the OpenPosture model, the developers sampled 20 photos and compared the predicted results to the actual results for kneeling, back position, neck position, and hand position static photos. The developers compared each of the postures to each other to determine which one performed best and why. The metrics captured are confusion matrix related data points, included True Positive, True Negative, False Positive, False Negative, Recall, Precision, Sensitivity, and Specificity. In this model, positive values represent optimal postures.

The below confusion matrix for kneeling, **Image 1**, offers an overview of the classification performance in distinguishing between two postural states: "Kneeling" and "Not Kneeling,” where "Kneeling" represents a seated posture where the toes are positioned behind the knees, and "Not Kneeling" signifies an optimal posture. The matrix reveals that out of the instances classified as "Kneeling", the model correctly identified 2 cases (True Negative), while incorrectly classifying 0 as "Not Kneeling" (False Positive). Conversely, among the instances labeled as "Not Kneeling", the model correctly identified 16 cases (True Positive) but misclassified 2 as "Kneeling" (False Negative). As such, the model correctly classified 90% of the sample, or 18/20 kneeling instances. Refer to **Image 4** for precision, recall, specificity, and sensitivity for kneeling. Reasons for the inaccurate values are because the position of the knees versus the toes are midway between kneeling and not kneeling.

A close-up of a sign

Description automatically generated

Image 1

The below confusion matrix for back position, **Image 2**, offers an overview of the classification performance in distinguishing between two postural states: "Hunched/Reclined" and "Straight,” where "Hunched/Reclined" represents a seated posture where the back is angled forward or backwards, and "Straight" signifies an optimal posture. The matrix reveals that out of the instances classified as "Hunched/Reclined", the model correctly identified 12 cases (True Negative), while incorrectly classifying 0 as "Straight" (False Positive). Conversely, among the instances labeled as "Straight", the model correctly identified 8 cases (True Positive),and misclassified 0 as "Hunched/Reclined" (False Negative). As such, the model correctly classified 100% of the sample, or 20/20 back position instances. Refer to **Image 5** for precision, recall, specificity, and sensitivity for back position. Reasons for all accurate classifications is because the images sampled clearly capture straight, reclined, and hunched postures.

A close-up of a sign

Description automatically generated

Image 2

The below confusion matrix for hand position, **Image 3**, offers an overview of the classification performance in distinguishing between two postural states: "Folded" and "Not Folded,” where "Folded" represents a seated posture where the hands are crossed and potentially misaligning the spine, and "Not Folded" signifies an optimal posture. The matrix reveals that out of the instances classified as "Folded", the model correctly identified 3 cases (True Negative), while incorrectly classifying 0 as "Not Folded" (False Positive). Conversely, among the instances labeled as "Not Folded", the model correctly identified 14 cases (True Positive), and misclassified 3 as "Folded" (False Negative). As such, the model correctly classified 85% of the sample, or 17/20 hand position instances. Refer to **Image 5** for precision, recall, specificity, and sensitivity for hand position. Reasons for inaccurate classifications is because the images sampled captured arms that were parallel and thus indistinguishable.

A close-up of a sign

Description automatically generated

Image 3

The below confusion matrix for neck position, **Image 4**, offers an overview of the classification performance in distinguishing between two postural states: "Forward/Backward" and "Straight,” where "Forward/Backward" represents a seated posture where the neck is angled downwards or upwards and potentially causing neck pain crossed, and "Straight" signifies an optimal posture. The matrix reveals that out of the instances classified as "Forward/Backward", the model correctly identified 4 cases (True Negative), while incorrectly classifying 2 as "Straight (False Positive). Conversely, among the instances labeled as "Straight", the model correctly identified 14 cases (True Positive) and misclassified 0 as "Forward/Backward" (False Negative). As such, the model correctly classified 90% of the sample, or 18/20 neck position instances. Refer to **Image 4** for precision, recall, specificity, and sensitivity for neck position. Reasons for inaccurate classifications are because the position of the neck was in between straight vs forward or backward and thus not clearly distinguishable.

A close-up of a sign

Description automatically generated

Image 4

As shown in **Image 5**, the metrics vary across different posture elements due to differences in classification accuracy and the ability of the model to correctly identify instances of each posture. In terms of precision, "Kneeling", "Back", and "Hands" all achieved a perfect score of 100%, indicating that when the model predicts these postures, it is highly accurate. "Back" had the highest recall, specificity, sensitivity, and percent correct, suggesting that it performed optimally in terms of both identifying true positive and true negative instances, resulting in a flawless classification. "Hands" had a slightly lower recall and sensitivity compared to "Kneeling" and "Back", indicating that it might have missed identifying some true positive instances. However, it still maintained a high precision, resulting in a relatively high percent correct. "Neck" had a relatively high precision but lower specificity, suggesting that while it correctly identified many positive instances, it also misclassified some negative instances. However, its overall classification accuracy, as indicated by percent correct, was still quite high. Overall, based on the provided metrics, "Back" appears to be the most optimal posture element as it achieved perfect scores across all metrics, indicating flawless classification performance.

A screenshot of a table

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Image 5

Precision measures the accuracy of positive predictions. In this model, high precision means that when the model predicts a posture as optimal, it is highly likely to be correct. High precision ensures that the model minimizes false positives, meaning it is less likely to incorrectly classify non-optimal postures as optimal and prevents the provision of incorrect guidance or feedback to the user. Kneeling, back, and hands have a higher precision than neck, indicating a more favorable performance for kneeling, back, and hands.

Recall (Sensitivity) measures the ability of the model to correctly identify all optimal posture instances. High recall indicates that the model effectively captures all instances of the optimal posture from the dataset. High recall ensures that the model does not miss identifying any instances of the desired posture, minimizing the risk of failing to provide feedback or guidance when the user is in the optimal position. Back and neck performed the best, kneeling performed third best, and hands performed third best.

Specificity measures the ability of the model to correctly identify all non-optimal instances. In this model, high specificity means that the model effectively distinguishes non-optimal postures from the optimal one. This ensures that when the user is not in the optimal posture, the model correctly identifies this condition, preventing false alarms or incorrect feedback. All posture elements performed perfectly except for the neck, indicating that the model may suggest incorrect recommendations for neck posture. In this model, specificity is likely the most important accuracy measure because it enables users to be correctly provided feedback for non-optimal postures.

The OpenPosture developers originally intended to compare the performance metrics from the static photos to the performance metrics of the live video recording. However, the developers struggled to adequately capture metrics recorded over a period, as the model continuously captures data. The OpenPosture developers will leave the performance metrics for live results for future work. Despite not capturing the results for live results, the OpenPosture developers recognized that the results are very similar to the high accuracy of the static photos because the model is the same. In the future, the OpenPosture developers also intend to fine tune the model so that it detects parallel hands and in between neck and kneeling positions.