Short Summary of Pose Classification Project Method Choice

For this project, we opted for Support Vector Machines (SVM) as our primary classification method. The decision was driven by SVM's robustness in high-dimensional spaces, which is particularly relevant given the nature of our data—33 keypoints of the human body resulting in a high-dimensional feature space. SVM's capacity to efficiently handle both linear and non-linear separations through the use of kernel tricks further motivated its selection. This versatility is crucial in pose classification, where the differentiation between classes might not always be linearly discernable based on the keypoints alone.

Limitations

Despite its strengths, our approach with SVM faces several limitations:

Data Imbalance: The dataset exhibits a class imbalance, with certain poses represented more frequently than others. This imbalance can lead to a model that is biased toward the more common classes, potentially reducing its overall accuracy and generalization capability to less frequent poses.

Feature Utilization: The current model relies solely on raw keypoints as features. This approach may not fully capture the complexities and nuances of human poses, as relationships between keypoints, such as angles and distances, contain valuable information for classification.

Scalability and Complexity: While SVMs are powerful, they can become computationally intensive as the dataset size increases, especially when using complex kernels. This scalability issue could pose challenges in operational environments requiring real-time predictions.

Improvement Suggestions

Data Augmentation: To address the issue of class imbalance, data augmentation techniques such as rotations, scaling, and mirroring could generate additional training examples for underrepresented classes, thereby enhancing the model's robustness and accuracy.

Advanced Feature Engineering: Incorporating derived features like distances and angles between keypoints could provide the model with a richer set of information to learn from, potentially improving its ability to distinguish between similar poses.

Exploring Deep Learning:Transitioning to deep learning models, specifically Convolutional Neural Networks (CNNs), could offer significant improvements. CNNs are adept at capturing spatial hierarchies in data, making them exceptionally suited for tasks involving image and keypoint data. Implementing a CNN could also facilitate the direct use of raw images alongside keypoints, further enriching the model's input.

Hyperparameter Tuning and Model Selection: A thorough exploration of SVM hyperparameters and kernel choices could yield performance gains. Additionally, experimenting with different machine learning models and ensemble techniques might uncover more effective approaches for this specific classification task.

In conclusion, while the SVM-based approach establishes a solid foundation for pose classification, exploring these avenues for improvement could lead to enhanced performance and more robust pose recognition capabilities.