Discussion: Analysis of KNN Classifier Performance

Distance Metric Comparison and Dataset Characteristics:

The performance comparison between the L1 (Manhattan) and L2 (Euclidean) distance metrics was conducted on a balanced dataset consisting of 300 images (100 each for Cat, Dog, and Panda). The 5fold cross validation results clearly demonstrated the superiority of the L1 metric.

Optimal Metric	Peak Accuracy	Rationale
L1 (Manhattan)	$\approx$ 43.8 % (at K =25)	Better suited for high dimensional data where features (raw pixels) are noisy and potentially non-independent. L1 is less sensitive to large, isolated differences in single dimensions.
L2 (Euclidean)	$\approx$ 39.7% (at K =7)	Its performance suffered due to the Curse of Dimensionality in the 1024 dimensional feature space, as it exaggerates large differences (due to squaring) and leads to diminished feature discrimination.

Given that the feature vector consists of 1024 raw grayscale pixel values, this space is considered high-dimensional and noisy. For such data, the L1 metric, which calculates the path distance by summing absolute differences, proved more effective than the L2 straight-line distance. The L1 metric provides a more reliable measure of similarity when dealing with the non-linear and high-variance nature of raw pixel data, where the difference in a single pixel's intensity might not be as critical as the cumulative difference across all pixels.

Complexity of Classes and Feature Nature:

The maximum achieved accuracy of approx 43.8% is only slightly better than the random chance baseline of 33.3% for a 3 class problem. This low performance, despite the dataset being perfectly balanced, points directly to the inadequacy of the feature representation used.

- **Feature Nature:** The features are raw pixel intensities, which are highly sensitive to variations in lighting, background, pose, and texture, all of which are common in real world images of animals (Cat, Dog, Panda).

- **Class Complexity:** Classifying animals requires recognizing complex local and global patterns (e.g., ears, whiskers, facial structure). The process of flattening the 32x32 image into a 1D vector destroys all spatial relationships between pixels, making it impossible for the simple KNN model to identify the structural features that distinguish a Cat from a Dog or a Panda.

Limitations and Potential Improvements:

The primary limitation is the loss of spatial context during preprocessing. To enhance classification accuracy significantly, the following improvements are crucial:

- **Feature Engineering:** Instead of raw pixels, apply a robust local feature descriptor to capture spatial information. Techniques like Histogram of Oriented Gradients (HOG) or Local Binary Patterns (LBP) can summarize gradients and texture, respectively, providing the KNN classifier with more discriminative features that are less sensitive to noise.

- **Model Choice:** The most significant improvement would be to transition from KNN to a Convolutional Neural Network (CNN). A CNN is designed to operate on the 2D image structure, automatically learning hierarchical features (edges, shapes, object parts) that are essential for distinguishing between Cat, Dog, and Panda classes.

- **Dimensionality Management:** If staying with the KNN model, apply Principal Component Analysis (PCA) to the 1024-dimensional feature vectors. PCA would transform the data into a lower-dimensional subspace, mitigating the effects of the Curse of Dimensionality and potentially improving the separation between classes.