Model Development Phase Template

Date	15 April 2024
Team ID	738181
Project Title	CRIME VISION: ADVANCED CRIME CLASSIFICATION WITH DEEP LEARNING.
Maximum Marks	5 Marks

Model Selection Report

In the model selection report for future deep learning and computer vision projects, various architectures, such as CNNs or RNNs, will be evaluated. Factors such as performance, complexity, and computational requirements will be considered to determine the most suitable model for the task at hand.

Model Selection Report:

Model	Description
DenseNet121	The DenseNet121 model architecture is utilized for this project. DenseNet is a convolutional neural network (CNN) architecture known for its efficient use of parameters and feature reuse. It consists of densely connected blocks where each layer is connected to every other layer in a feed-forward fashion. The DenseNet architecture is compatible with transfer learning, enabling the use of pre-trained models as feature extractors. By integrating DenseNet121 into the crime classification task, we can benefit from its powerful feature extraction capabilities while adapting it to the specific requirements of the project.

Xception	Xception is a deep convolutional neural network architecture known for it is depth-wise separable convolutions. It follows a modified Inception module, replacing standard convolutions with depth-wise separable convolutions, which significantly reduces the number of parameters and computational complexity while maintaining or even improving performance.
VGG16	VGG16 is a deep convolutional neural network architecture characterized by its simplicity and uniform architecture. It consists of multiple convolutional layers followed by max-pooling layers and fully connected layers. Despite its simplicity, VGG16 has shown strong performance in image classification tasks, particularly on datasets with diverse and complex visual patterns.
ResNet50	ResNet50 is a deep convolutional neural network architecture known for its residual learning framework. It introduces skip connections, or shortcuts, that bypass one or more layers, allowing the network to learn residual mappings instead of directly learning the underlying mappings. This alleviates the vanishing gradient problem and enables training of very deep networks.