All models and encoders are saved as pickle using Joblib.

Dependency:

Windows 11 Pro 23H2

Python V3.11.5

Package Used:

Numpy V1.26.0

Pandas V2.1.1

Joblib V1.1.1

Scikit-learn V1.3.1

Deploying a model in real-time for crime severity prediction is indeed a proactive approach to law enforcement. Here's an extended version of how this deployment strategy could work:

Real-time Deployment: The model is integrated into law enforcement systems to analyze incoming crime reports as soon as they are filed. This allows for immediate assessment of the severity of each crime.

Prediction and Prioritization: By analyzing various factors such as location, time, type of crime, and historical data, the model can provide a severity score or classification for each reported crime. Law enforcement agencies can then prioritize their response based on the predicted severity.

Feedback Loop: Once a crime is solved, the outcome is recorded. This outcome data is then fed back into the model as new training data. By continuously updating the model with real-world outcomes, it learns from its successes and failures, improving its accuracy over time.

Dynamic Adaptation: As the model learns from new data, it adapts to evolving crime patterns and trends. This allows law enforcement agencies to stay ahead of emerging threats and allocate resources more effectively.

Collaborative Efforts: Law enforcement agencies can collaborate to share data and insights generated by the model. This collaborative approach enhances the accuracy and effectiveness of crime prediction by leveraging a larger pool of data.

Ethical Considerations: It's essential to address ethical concerns related to privacy, bias, and fairness when deploying such a model. Safeguards must be in place to protect individuals' privacy rights and ensure that the model's predictions are fair and unbiased.
Transparency and Accountability: Law enforcement agencies should be transparent about how the model is used and ensure accountability for its decisions. Regular audits and evaluations can help identify any issues or biases in the model's predictions.
Continuous Improvement: The deployment of the model should be viewed as an iterative process. Regular evaluations and updates are necessary to maintain its accuracy and relevance in a changing environment.
By deploying the model in real-time and incorporating a feedback loop for continuous learning, law enforcement agencies can enhance their ability to prevent and combat crime more effectively while also fostering greater trust and transparency within the community.

F1 Score and accuracy score will be used to monitor the model. Accuracy is a straightforward metric that is easy to understand. It represents the proportion of correctly classified instances out of the total instances. Accuracy provides a clear indication of the overall performance of the model in terms of correct predictions. F1 score considers both precision and recall, making it robust to class imbalance. It provides a balanced assessment of the model's performance across different classes. Also, F1 score is suitable for datasets where the class distribution is skewed, as it focuses on the harmonic mean of precision and recall.

They model will be retrained at least every single day. As a simple model it only cost about 1 minute to train and the data will be added to the dataset once the crime is solved so the dataset is continually refreshing. This outcome data is then fed back into the model as new training data. By continuously updating the model with real-world outcomes, it learns from its successes and failures, improving its accuracy over time. This will also help the model to avoid drifting problems.