Model monitoring pipeline includes:

1. Data Ingestion and Preprocessing Monitoring:

- **Data Consistency Checks**: Ensure incoming data matches the expected format and types.
- **Data Drift Detection**: Monitor the statistical properties of incoming data and compare them with the training data. Algorithms that can be used include Population Stability Index(PSI) or olmogorov-Smirnov (KS) test.

2. Model Performance Monitoring:

- **Performance Metrics Tracking**: Continuously evaluate key performance metrics such as accuracy, precision, recall, F1 score, or mean squared error (MSE), depending on the problem type.

3. Model Drift Detection:

- **Concept Drift** occurs when there is a change in relationship between the input variable and output and can be detected by monitoring the model's predictions over time and comparing them with actual outcomes.
- **Performance Degradation Alerts**: Set thresholds for performance metrics, and trigger alerts if the metrics degrade beyond acceptable limits.

4. Logging and Reporting:

- **Comprehensive Logging**: Record all relevant data, including input features, predictions, and model outputs.
- **Automated Reporting**: Generate regular reports summarising the model's performance, data quality, and any detected drifts.

Model drift:

Model drift includes data and concept drift. Model drift can be tracked by the following steps, which include some that were mentioned in the model monitoring pipeline:

1. Define Baseline Performance: Establish a baseline performance level for the model using validation data or initial production data. This baseline serves as a reference for detecting deviations.

2. Monitor Key Metrics: Regularly monitor metrics such as prediction accuracy, precision, recall, and more. Set up alerts for significant deviations from the baseline.

3. Compare Distributions: Use statistical tests to compare the distributions of features and target variables over time. For example, the PSI can measure changes in the distribution of a variable between 2 datasets, while the KS test can determine if 2 sets of data come from the same distribution.

4. Feature Importance Monitoring: Track changes in feature importance scores over time. Significant shifts in feature importance may indicate changes in the underlying data patterns.

5. A/B Testing: Periodically test the current model against a challenger model on a portion of the data. This helps identify if the current model is underperforming compared to newer models.