Model Performance Evaluation and Ethical Reflection

This report evaluates the impact of different model parameters on performance metrics (AUC and R^2 score) using an SVM-based classifier on the Iris dataset with added noise.

Experiments:

- Models were trained with varying SVM kernels (linear vs RBF), different test set sizes (30% and 50%), and noise levels (0.5 and 1.0).
- Evaluation was conducted using average AUC (for classification) and R^2 (for regression-like interpretability).

Key Observations:

- RBF kernel slightly improved AUC but showed weaker R^2 scores, indicating possible overfitting or misalignment.
- A smaller test size improved R^2 scores but may reduce generalization.
- Reducing noise improved both AUC and R^2, confirming the negative impact of noisy features.

Results Summary:

- Linear kernel with low noise and 50% test size yielded better R^2.
- RBF with smaller test and low noise gave the best AUC (0.794).

Ethical, Legal, and Professional Reflection:

Legal Issues:

- Use of real data mandates strict data protection and regulatory compliance (e.g., GDPR).
- Misleading metrics can result in legal liabilities if used in decision-making processes (e.g., finance, health).

Ethical Concerns:

- Models must be fair and explainable; using high-noise or opaque models (like RBF) can increase algorithmic bias.
- Transparency in reporting model limitations is crucial to prevent harm.

Social Implications:

- Trust in machine learning is eroded if models perform poorly or unfairly.
- Unequal outcomes may emerge if models generalize poorly across demographics.

Professional Responsibilities:

- ML professionals must report and monitor models responsibly.
- Ensure validation, retraining, and ethical oversight are part of deployment pipelines.